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Stein

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(54) **AUTOMATIC PROCESSING SCALE ESTIMATION FOR USE IN AN IMAGE PROCESS**

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G06K 9/00 (2006.01)
G06K 9/34 (2006.01)

(52) **U.S. Cl.**
USPC **382/170**; 382/165

(58) **Field of Classification Search**
None
See application file for complete search history.

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Nielsen et al. "Segmentation of Soft Shadows based on a Daylight- and Penumbra Model." In: 5-8, 14-17 Computer Vision/Computer Graphics Collaboration Techniques. Mar. 30, 2007 [retrieved on Dec. 5, 2013). Retrieved from the Internet: <URL: http://www.cvmt.aau.dk/-cbm/onlinepapers/mirage07shadowremoval.pdf>.

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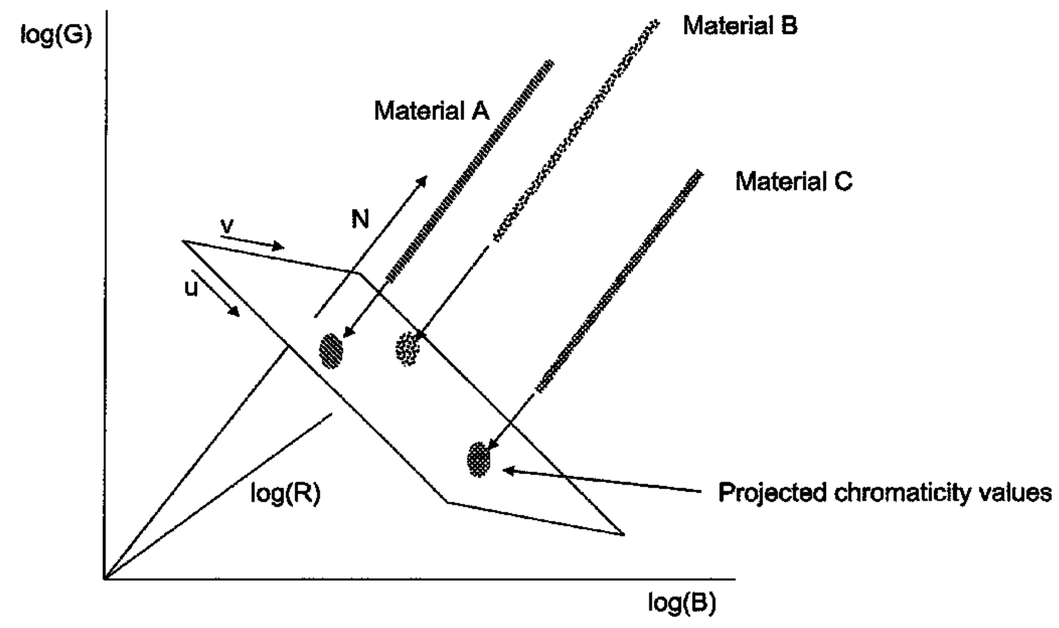
(57) **ABSTRACT**

In a first exemplary embodiment of the present invention, an automated, computerized method is provided for processing an image. According to a feature of the present invention, the method comprises the steps of providing an image file depicting an image, in a computer memory, calculating processing scale parameter information as a function of width dimension information for penumbrae depicted in the image; and generating intrinsic illumination and material reflectance images corresponding to the image using the processing scale parameter information.

18 Claims, 23 Drawing Sheets



Log Color Space Chromaticity Plane

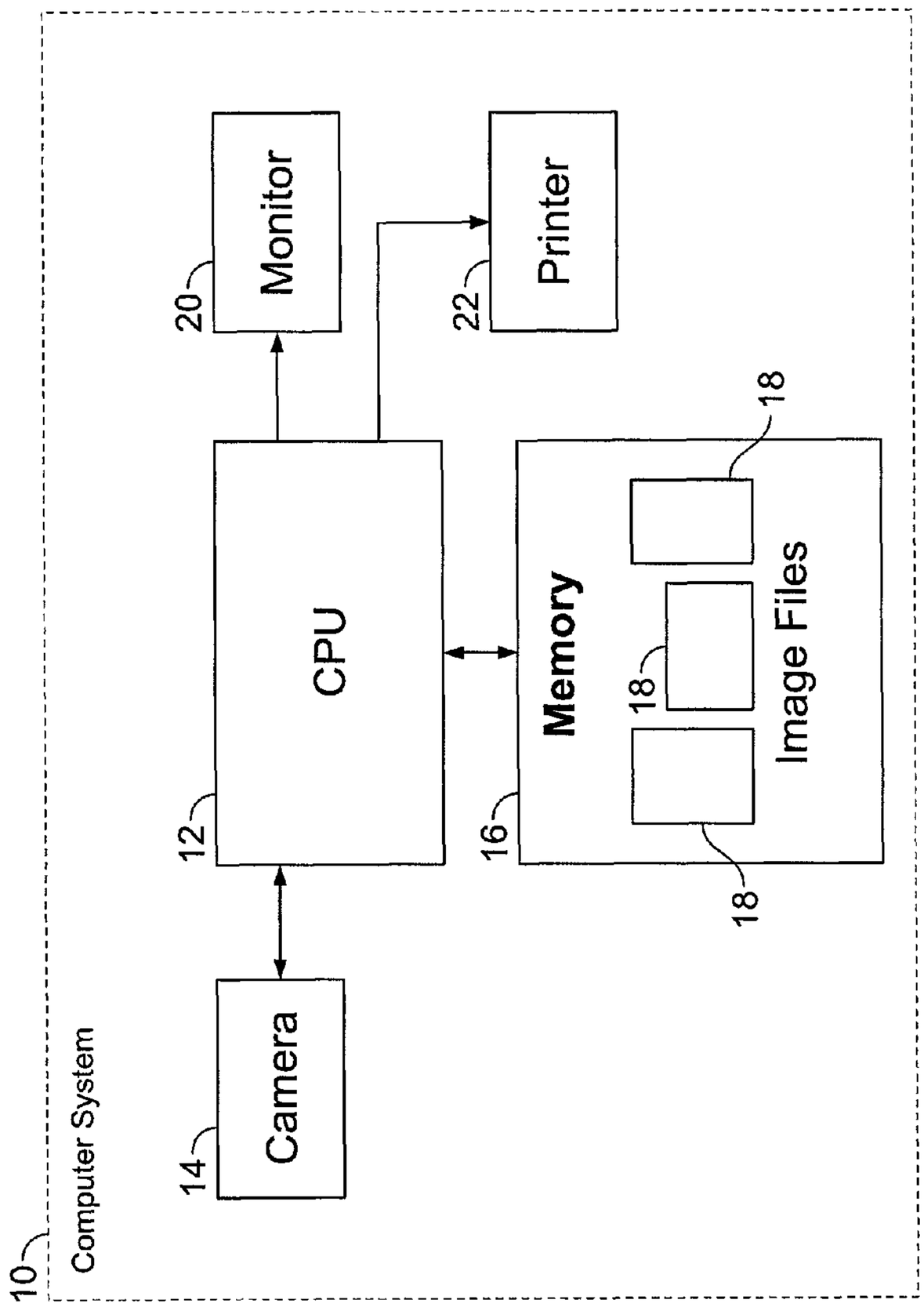

Computer System
10
Camera
14
CPU
12
Monitor
20
Printer
22
Memory
16
Image Files
18
18
18

FIG. 1

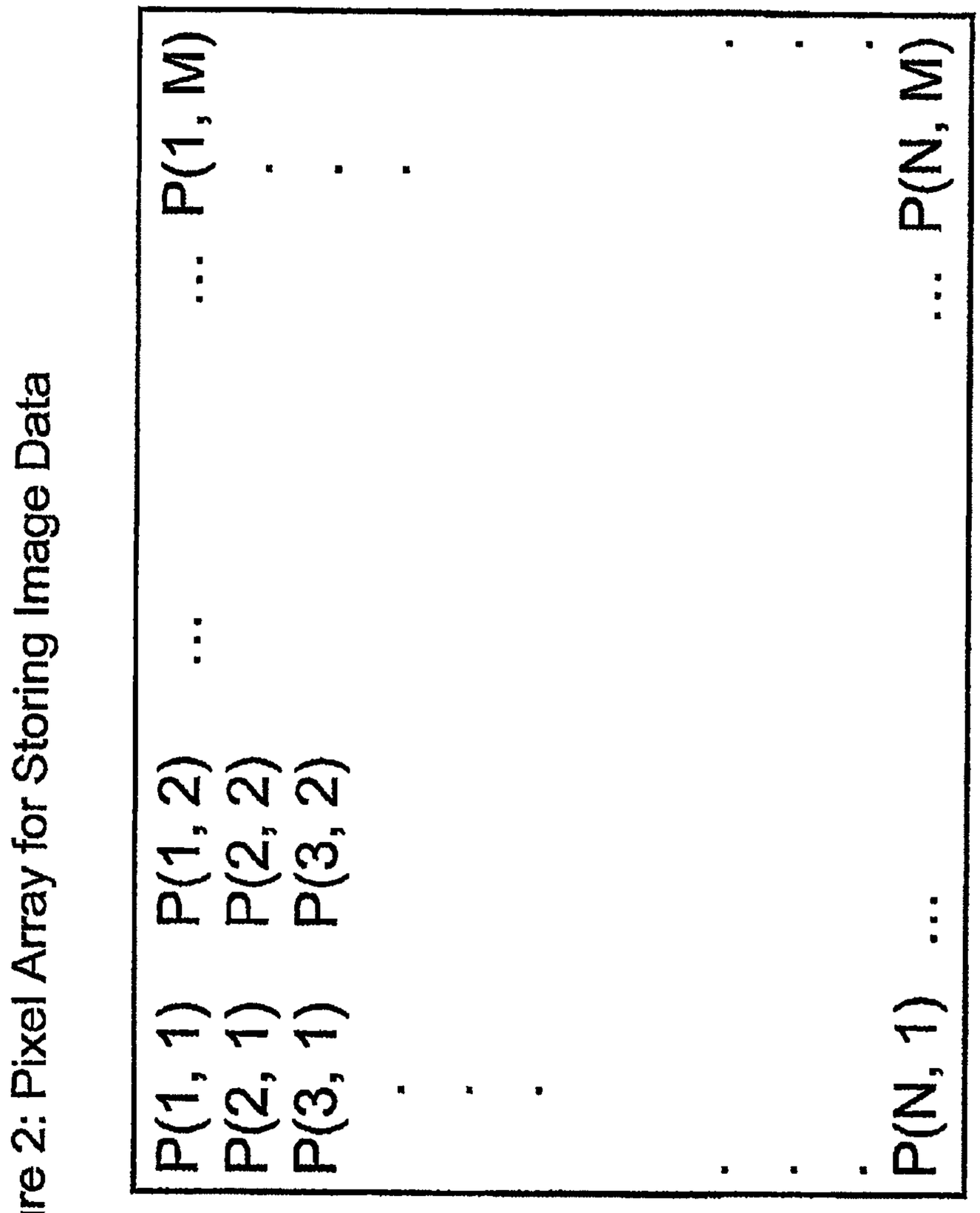


Figure 2: Pixel Array for Storing Image Data

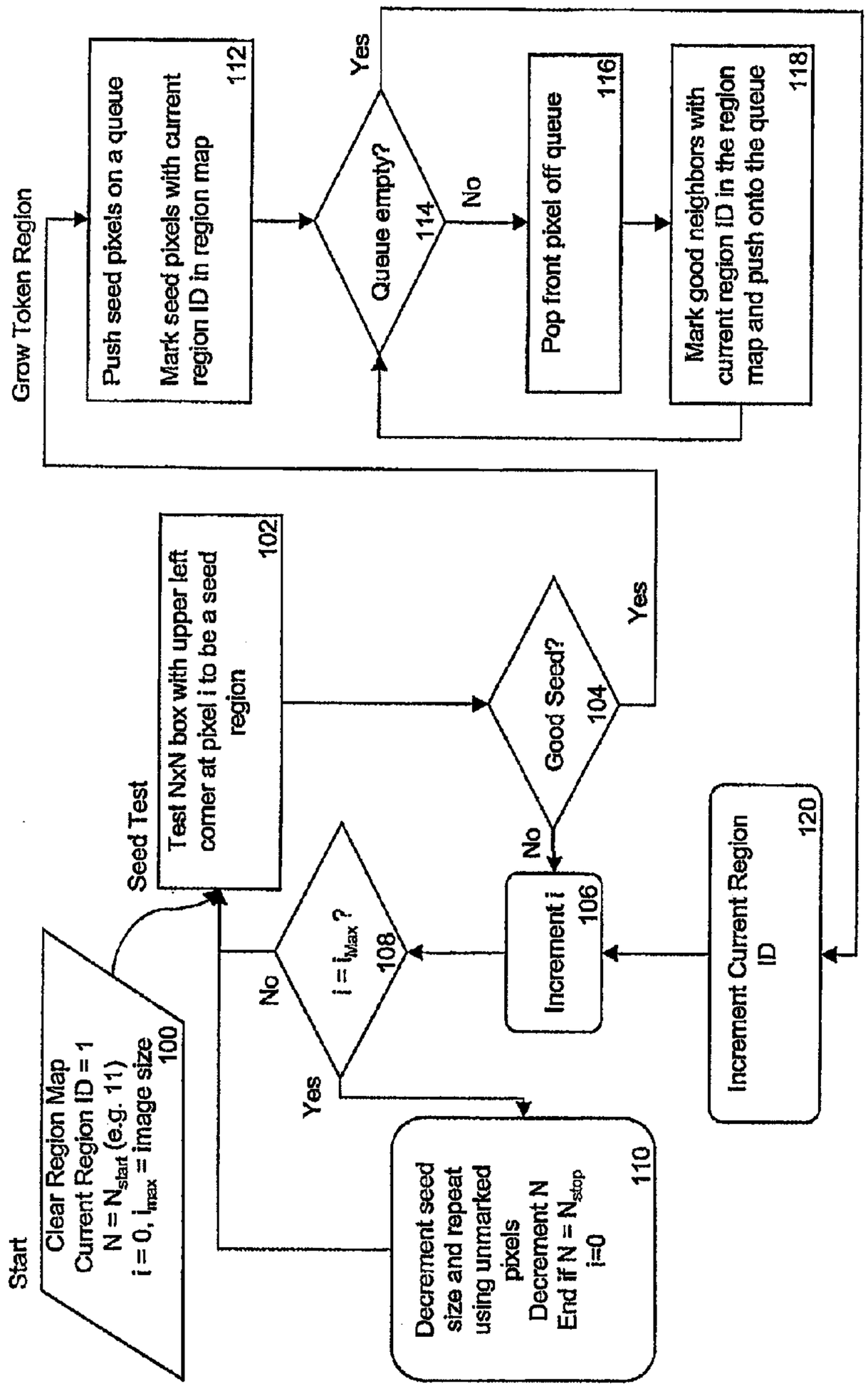


Figure 3A: Identifying Token Regions in an Image

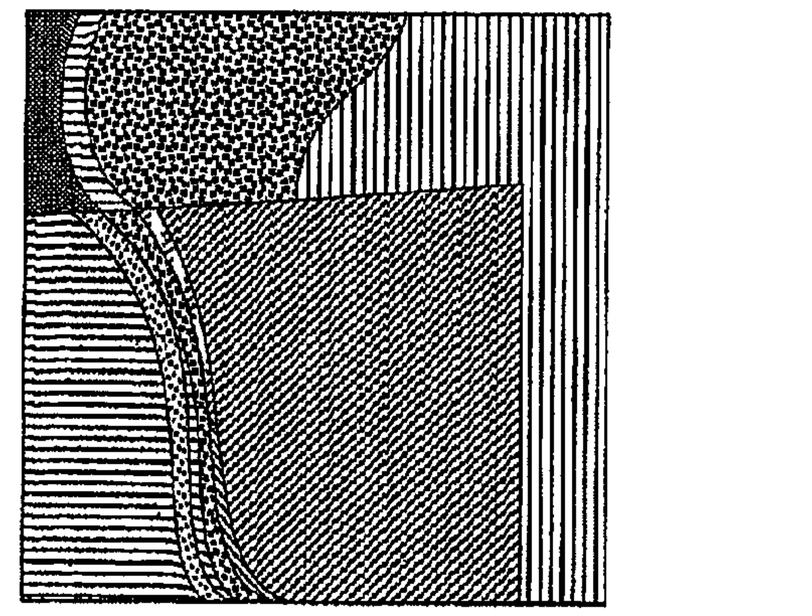


Figure 3C: Token Regions

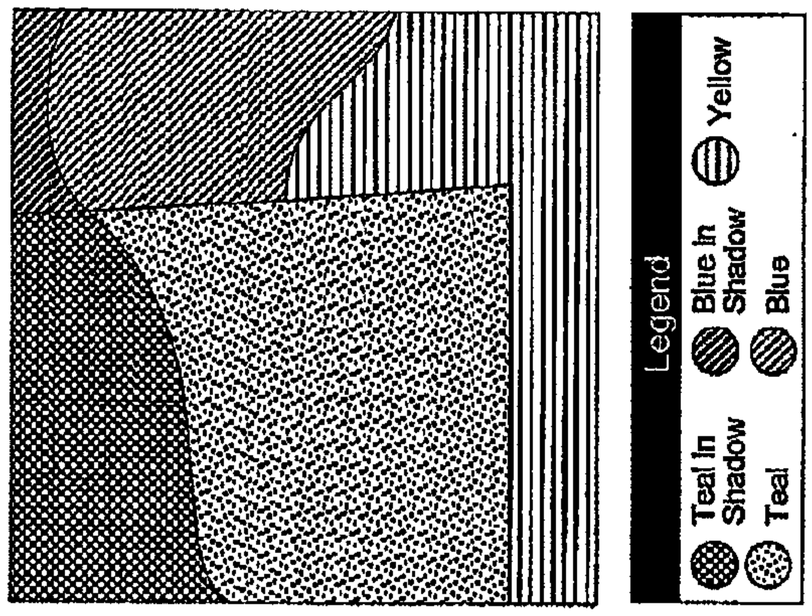


Figure 3B: Original Image

Figure 3B, 3C: Examples of Identifying Token Regions in an Image

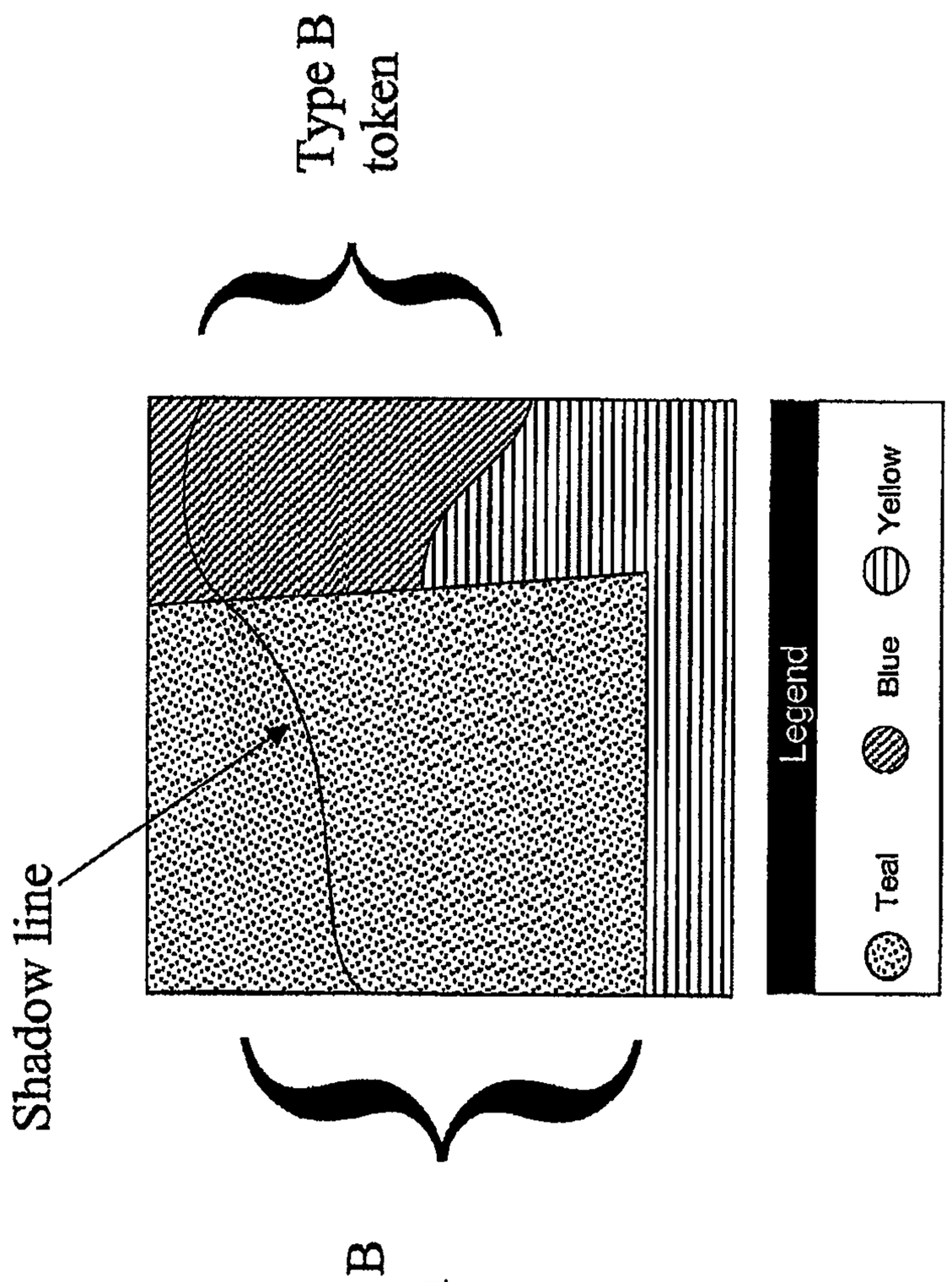


Figure 3D: Type B Tokens

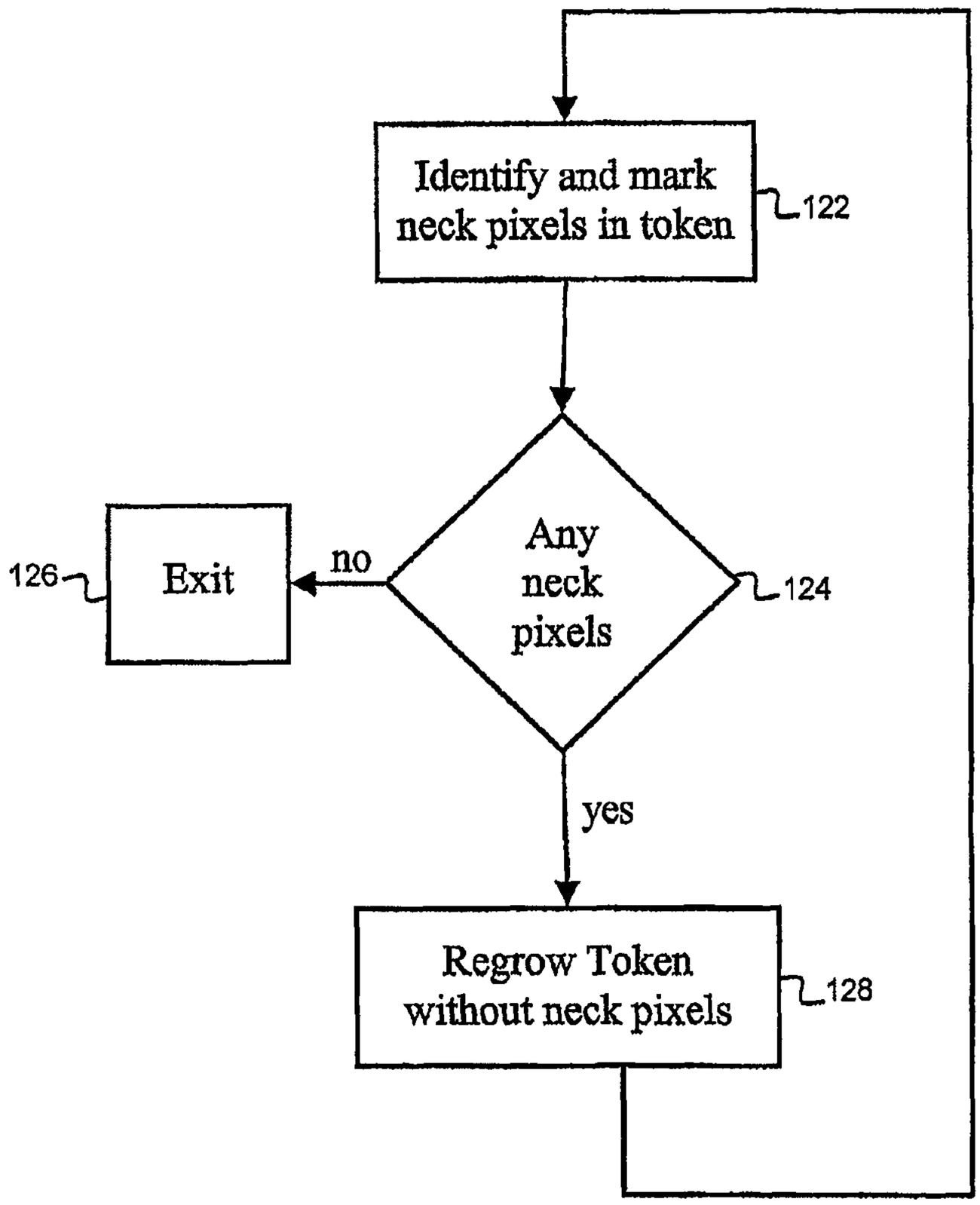
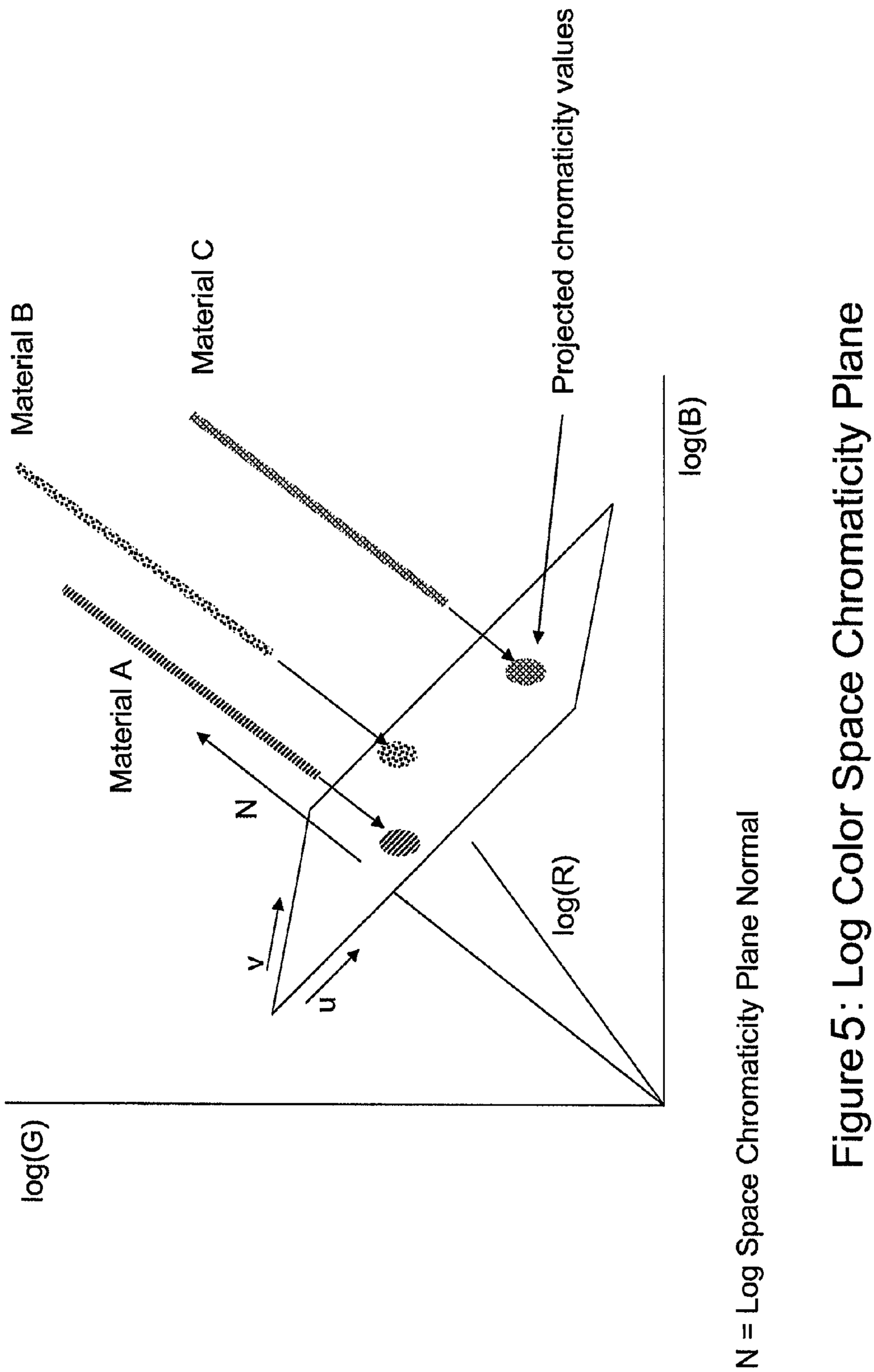

Identify and mark neck pixels in token
122
Any neck pixels
124
no
Exit
126
yes
Regrow Token without neck pixels
128

Figure 4



N = Log Space Chromaticity Plane Normal

Figure 5: Log Color Space Chromaticity Plane

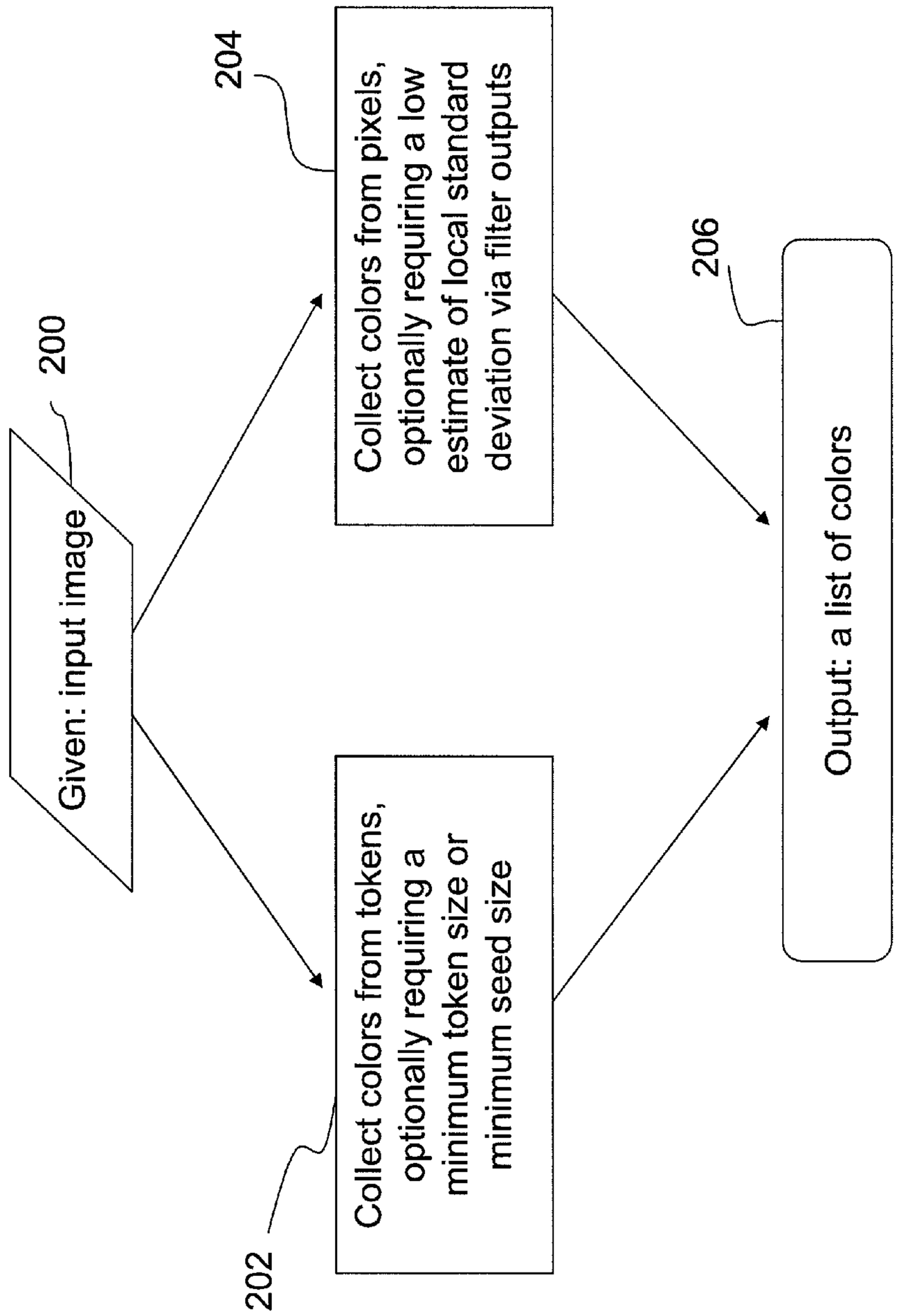


Figure 6: Selecting colors from an image

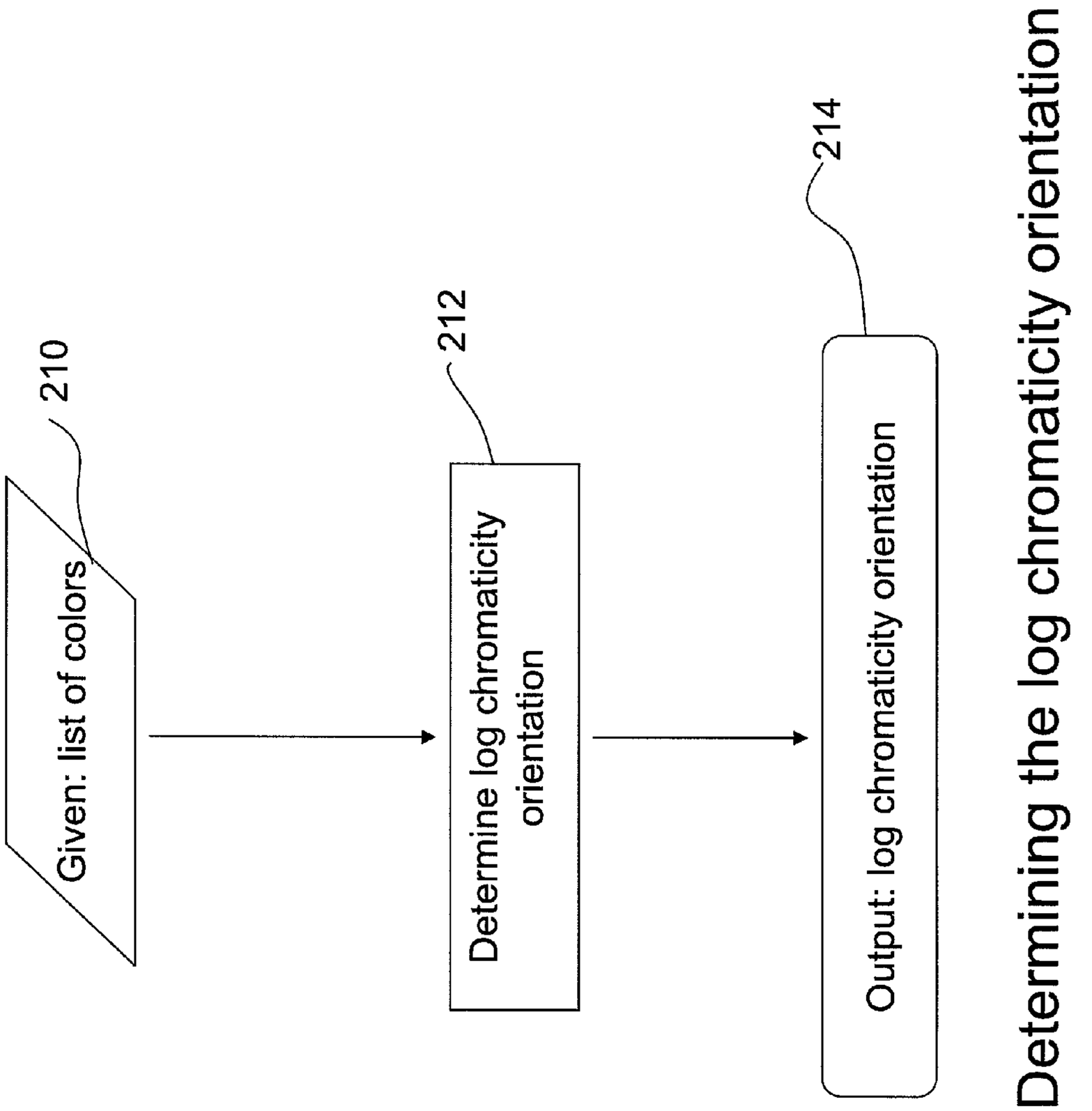


Figure 7: Determining the log chromaticity orientation

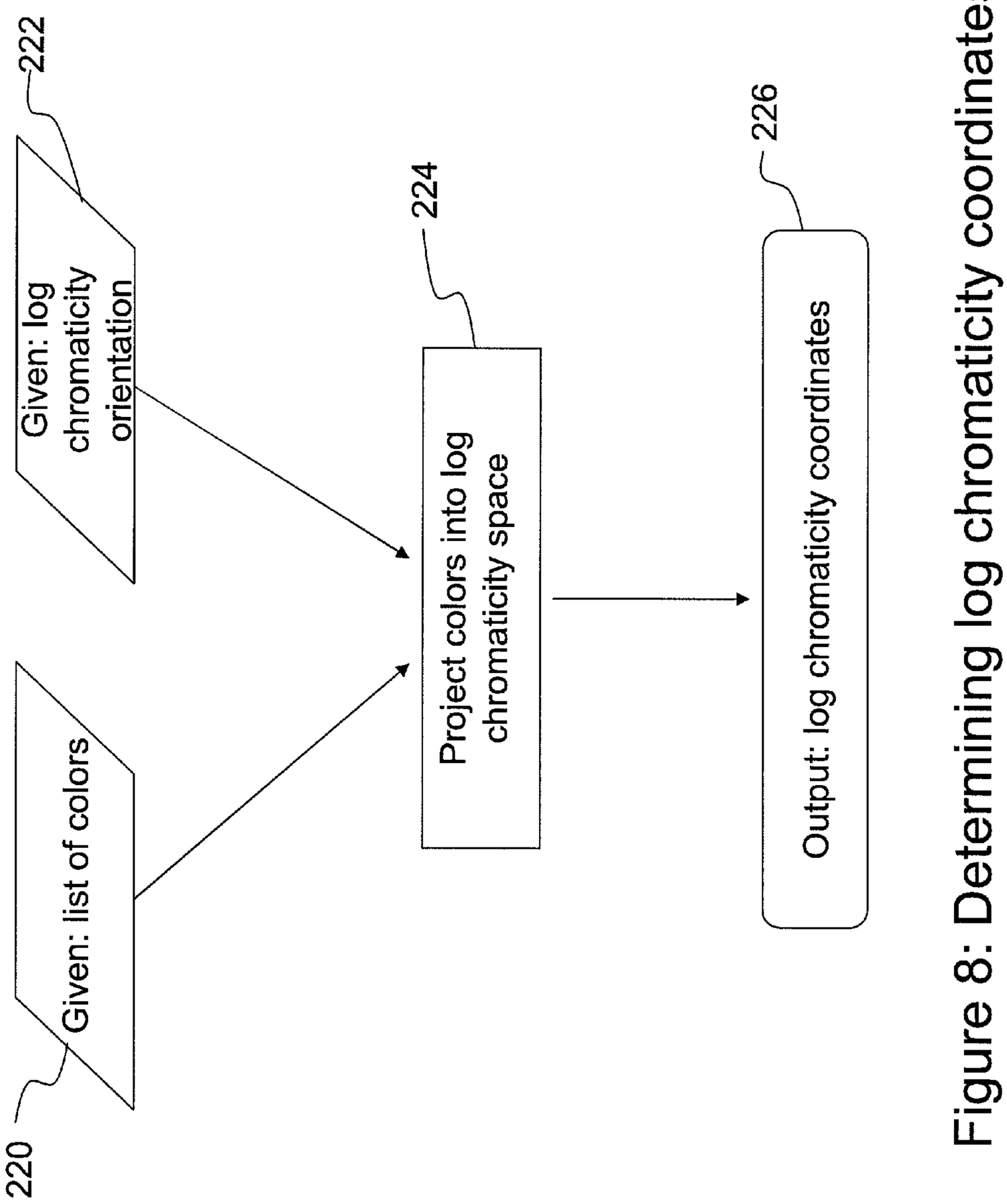


Figure 8: Determining log chromaticity coordinates

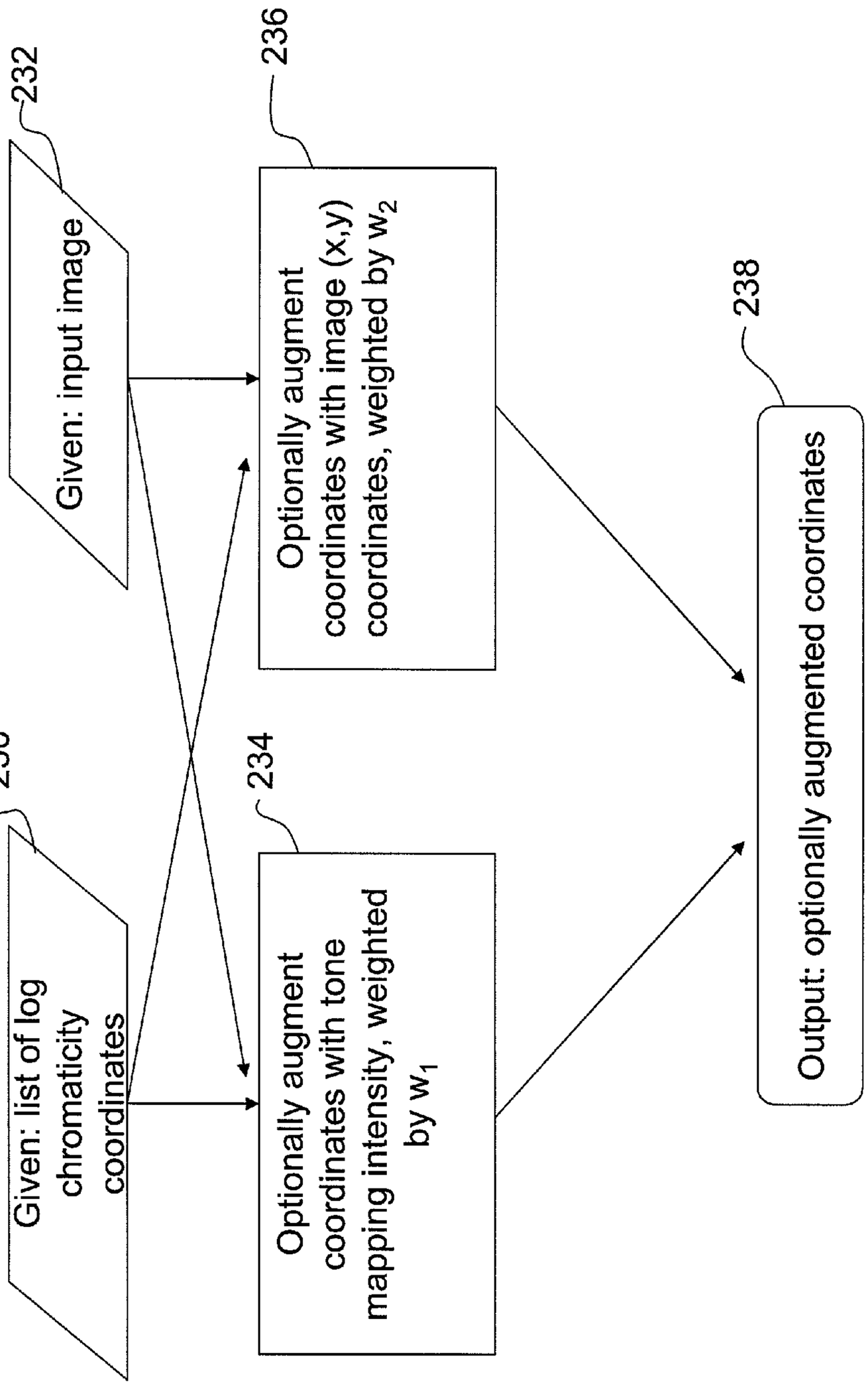


Figure 9: Optionally augmenting log chromaticity coordinates

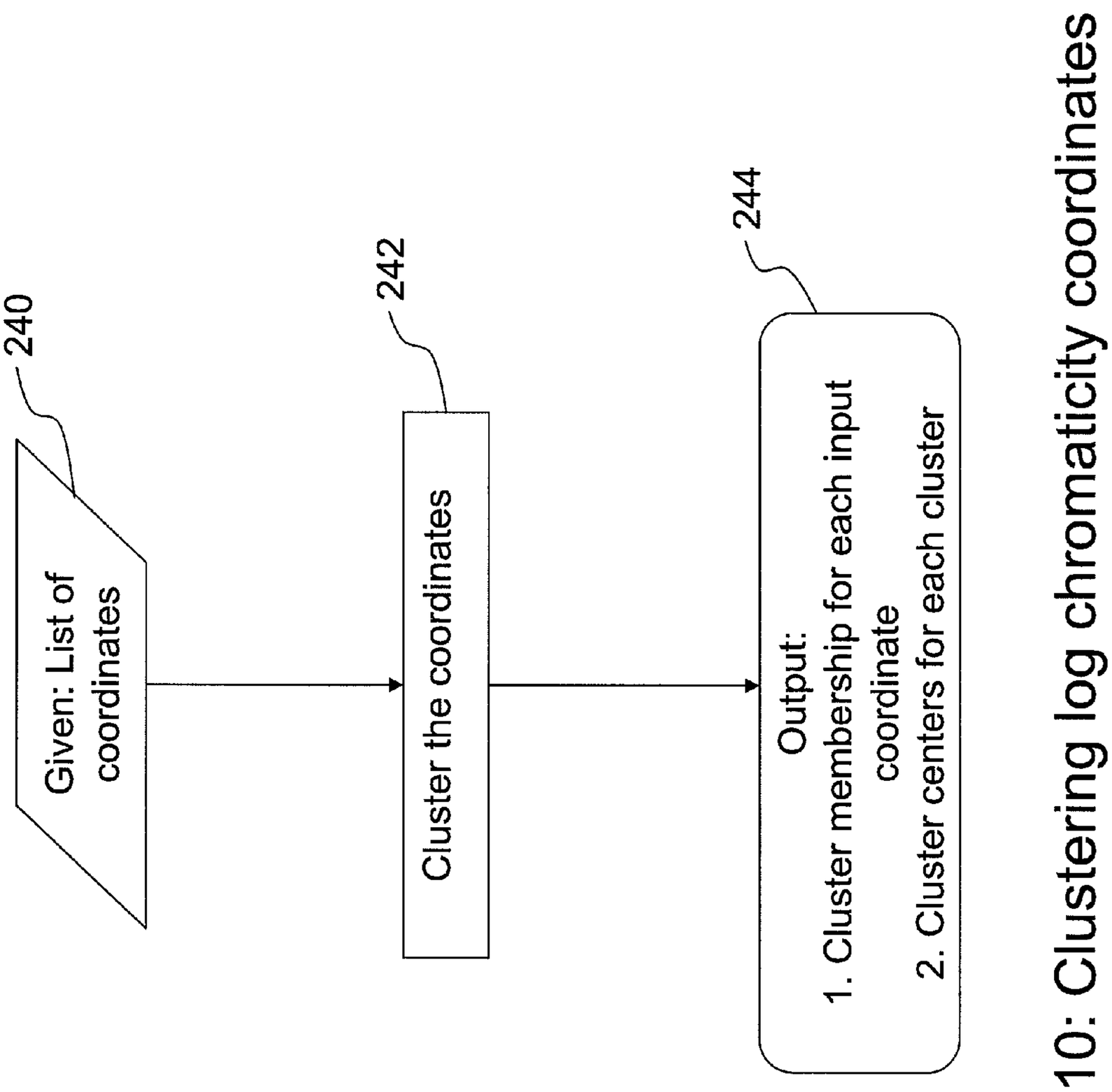


Figure 10: Clustering log chromaticity coordinates

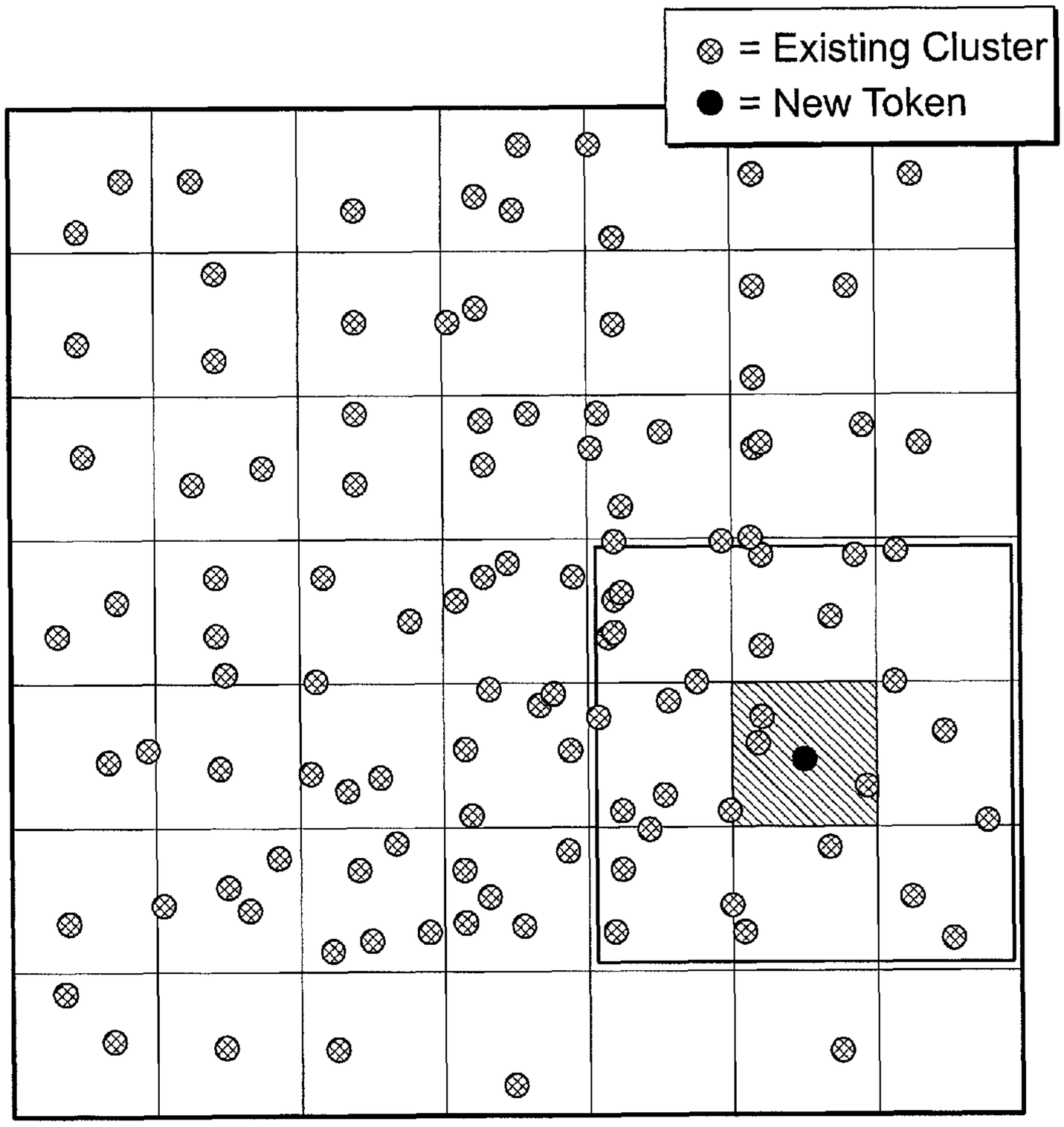


FIG. 10a

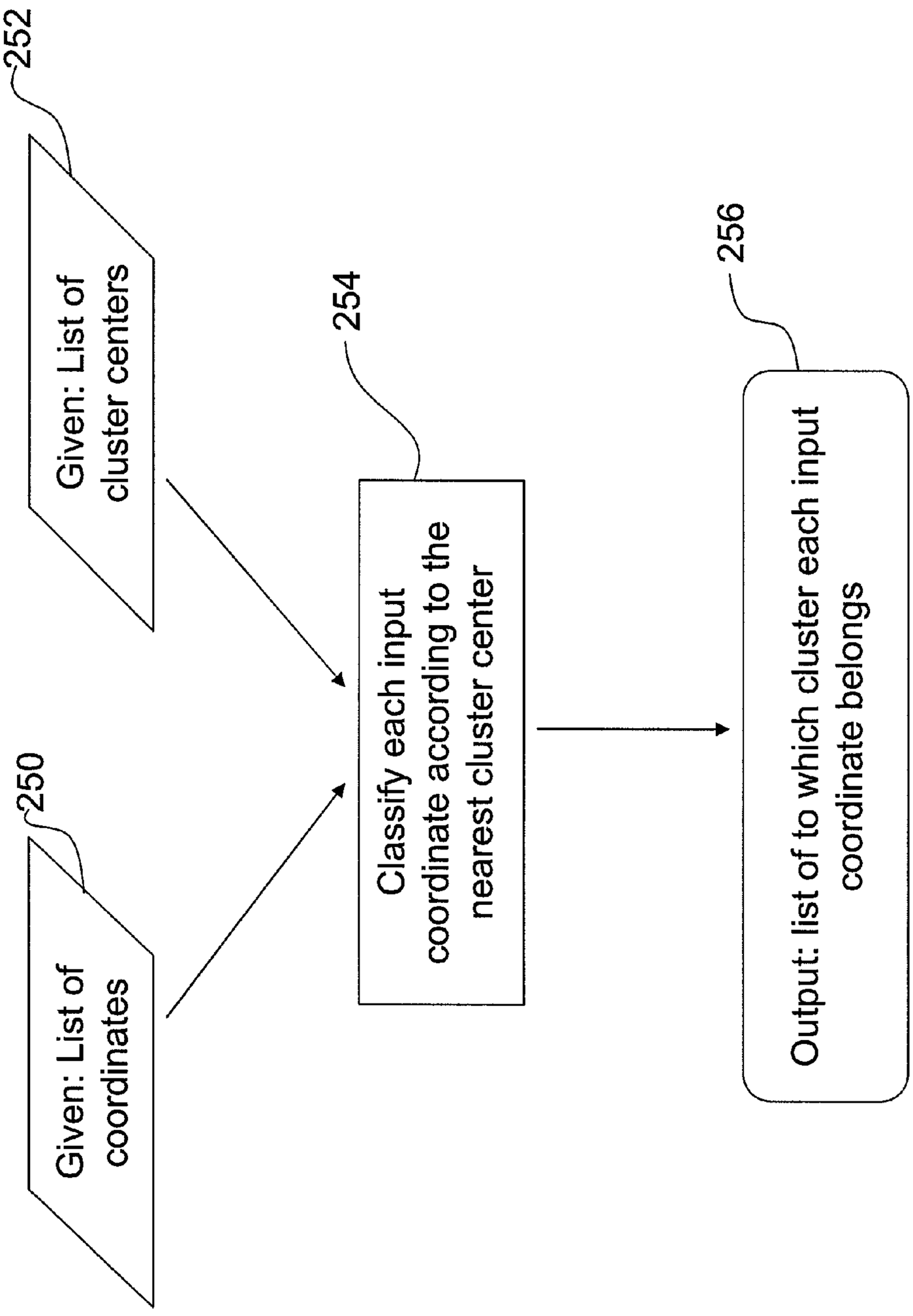


Figure 11: Assigning coordinates to clusters

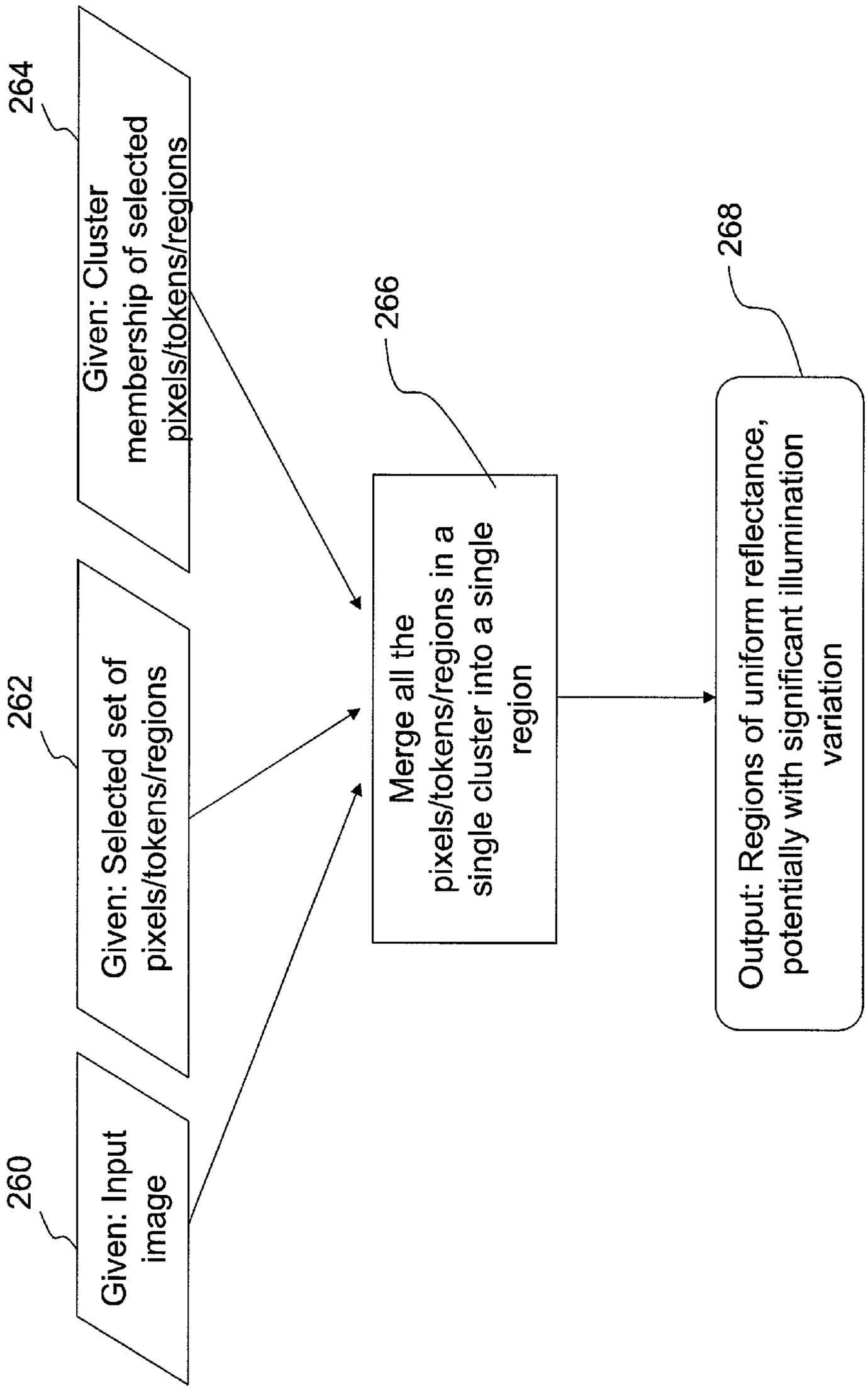
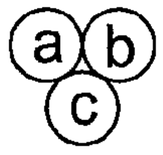


Figure 12: Detecting regions of uniform reflectance based on log chromaticity clustering



$$\begin{bmatrix} 1 & -1 & 0 \\ 1 & 0 & -1 \\ 0 & 1 & -1 \end{bmatrix} \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} = \begin{bmatrix} i_a - i_b \\ i_a - i_c \\ i_b - i_c \end{bmatrix}$$

$$[A] \qquad [x] = [b]$$

FIG. 13

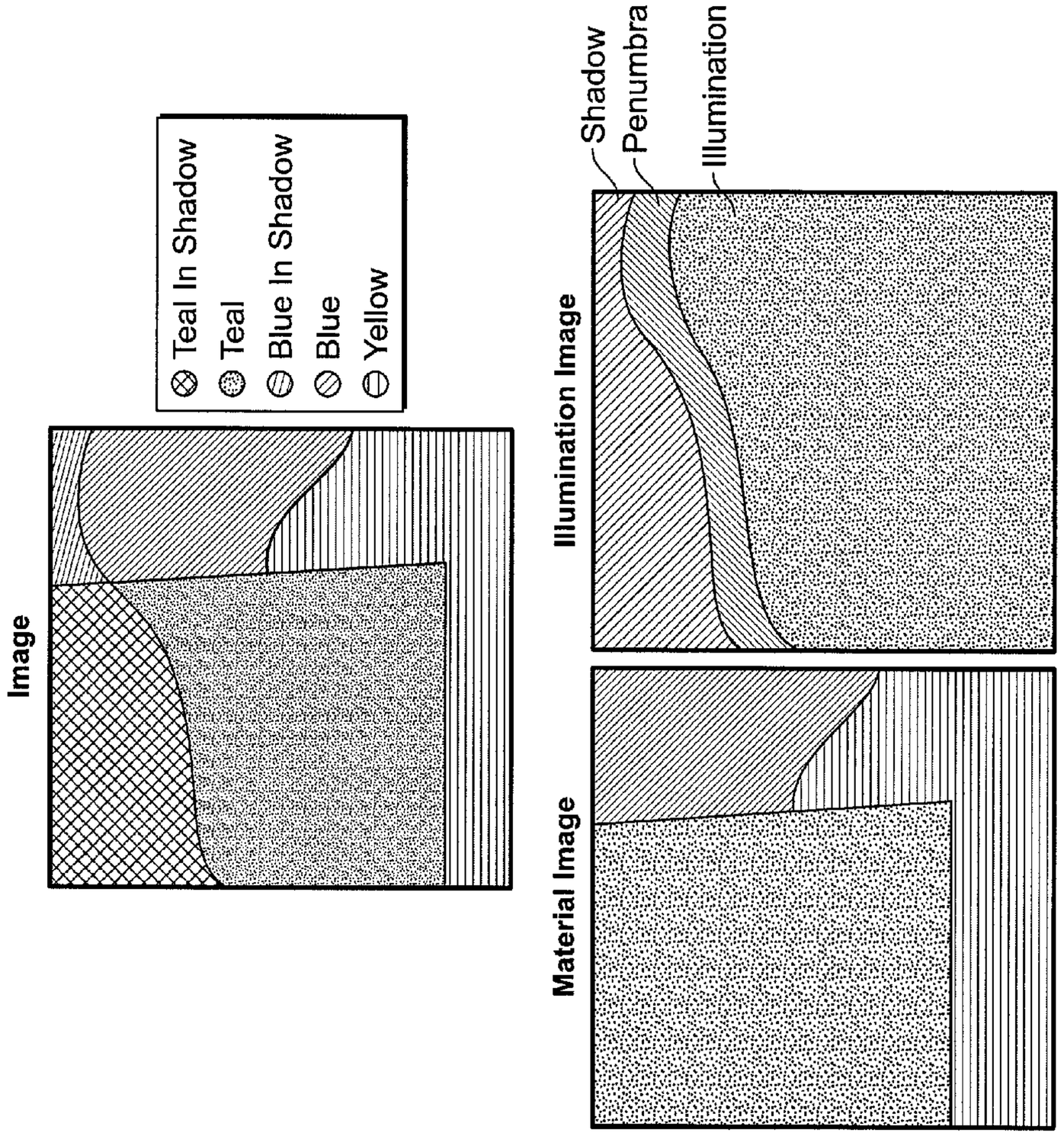


Image
Teal In Shadow
Teal
Blue In Shadow
Blue
Yellow
Illumination Image
Shadow
Penumbra
Illumination
Material Image

FIG. 14

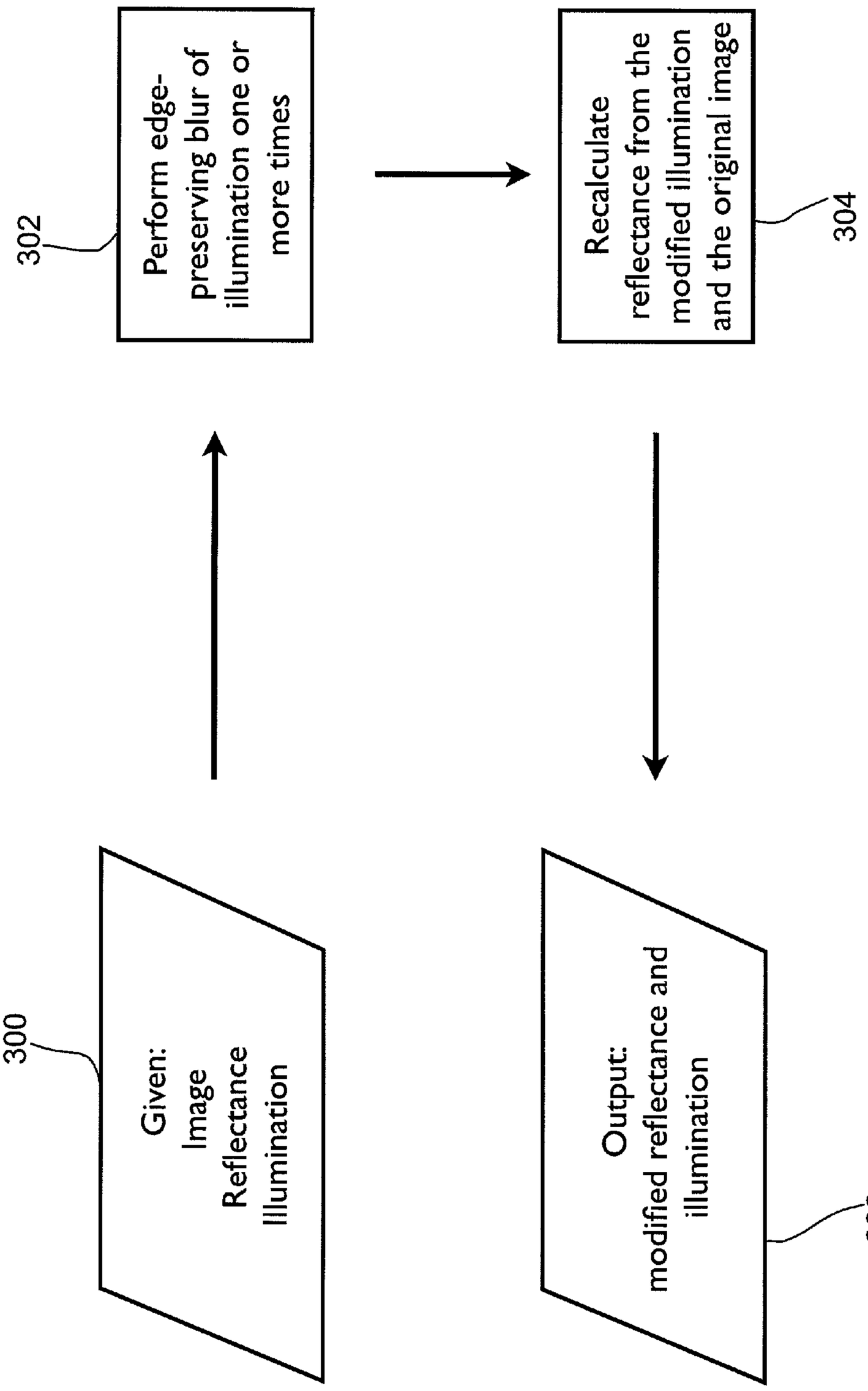

Given:
Image
Reflectance
Illumination
300
Perform edge-preserving blur of illumination one or more times
302
Recalculate reflectance from the modified illumination and the original image
304
Output:
modified reflectance and illumination
306

Figure 15

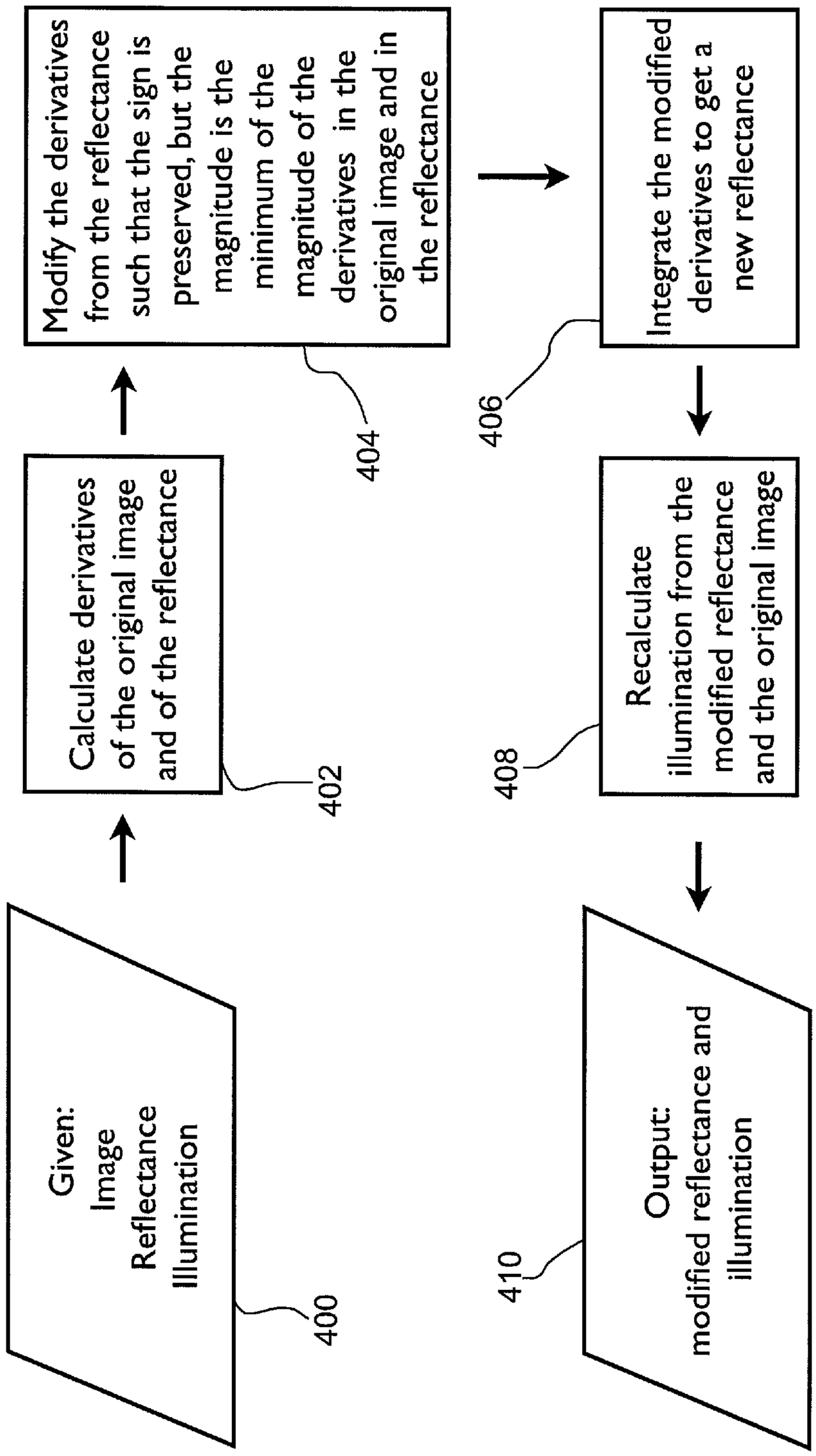

Given:
Image
Reflectance
Illumination
400
Calculate derivatives of the original image and of the reflectance
402
Modify the derivatives from the reflectance such that the sign is preserved, but the magnitude is the minimum of the magnitude of the derivatives in the original image and in the reflectance
404
Integrate the modified derivatives to get a new reflectance
406
Recalculate illumination from the modified reflectance and the original image
408
Output:
modified reflectance and illumination
410

Figure 16

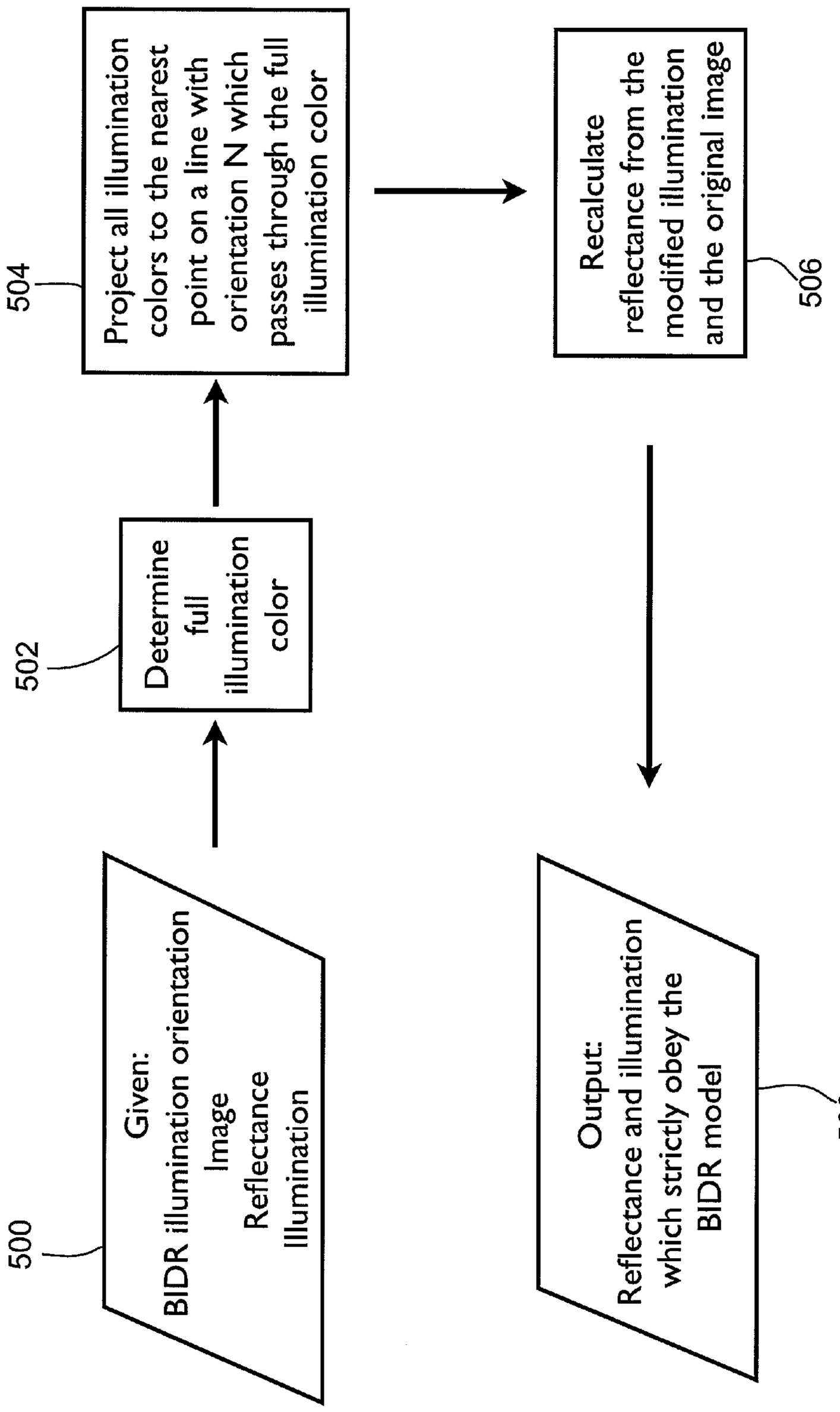

Given:
BIDR illumination orientation
Image
Reflectance
Illumination
500
Determine full illumination color
502
Project all illumination colors to the nearest point on a line with orientation N which passes through the full illumination color
504
Recalculate reflectance from the modified illumination and the original image
506
Output:
Reflectance and illumination which strictly obey the BIDR model
508

Figure 17

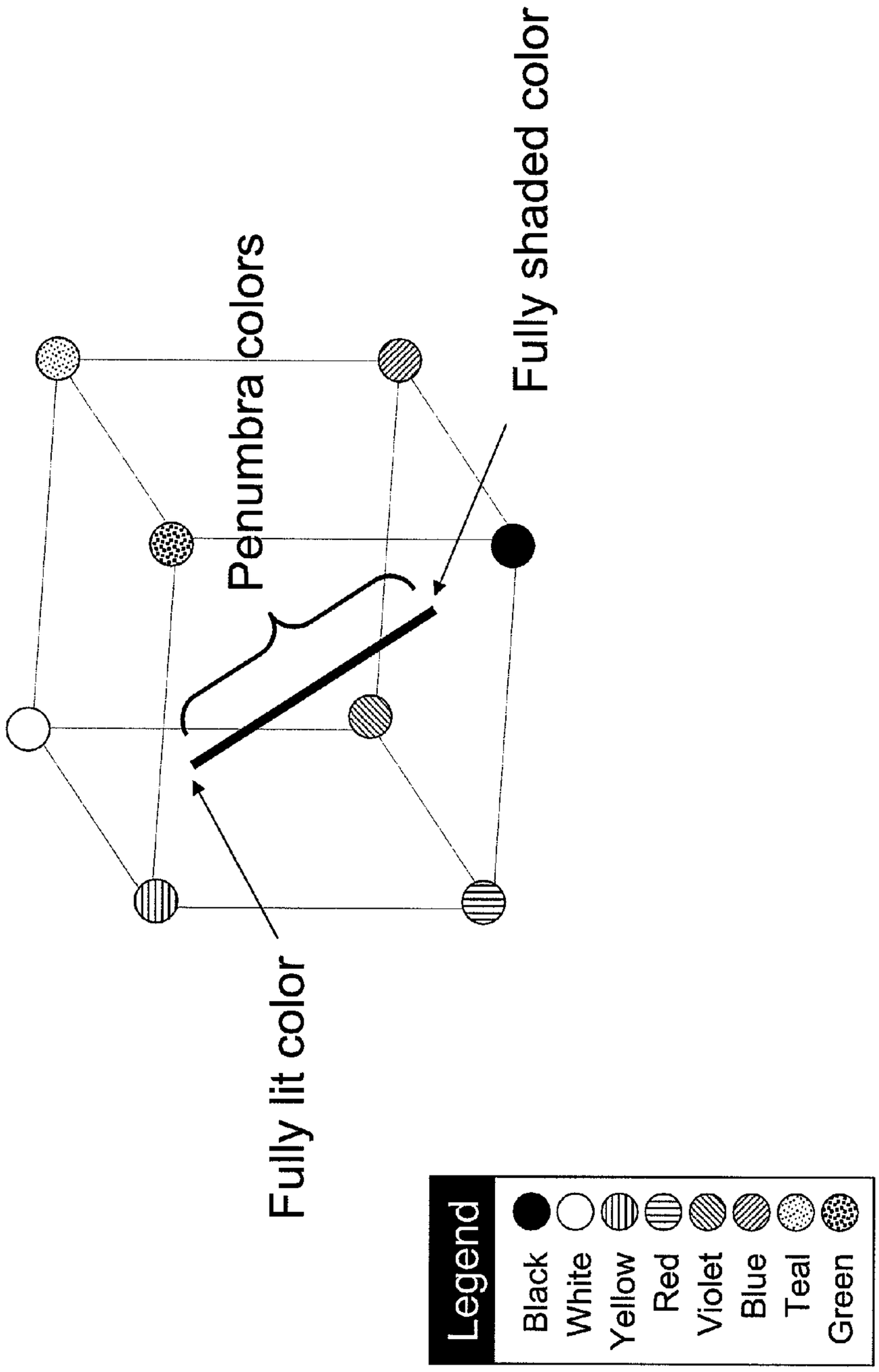

Representation of Body Reflection in RGB Space
Fully lit color
Penumbra colors
Fully shaded color
Legend
Black
White
Yellow
Red
Violet
Blue
Teal
Green

Figure 18:

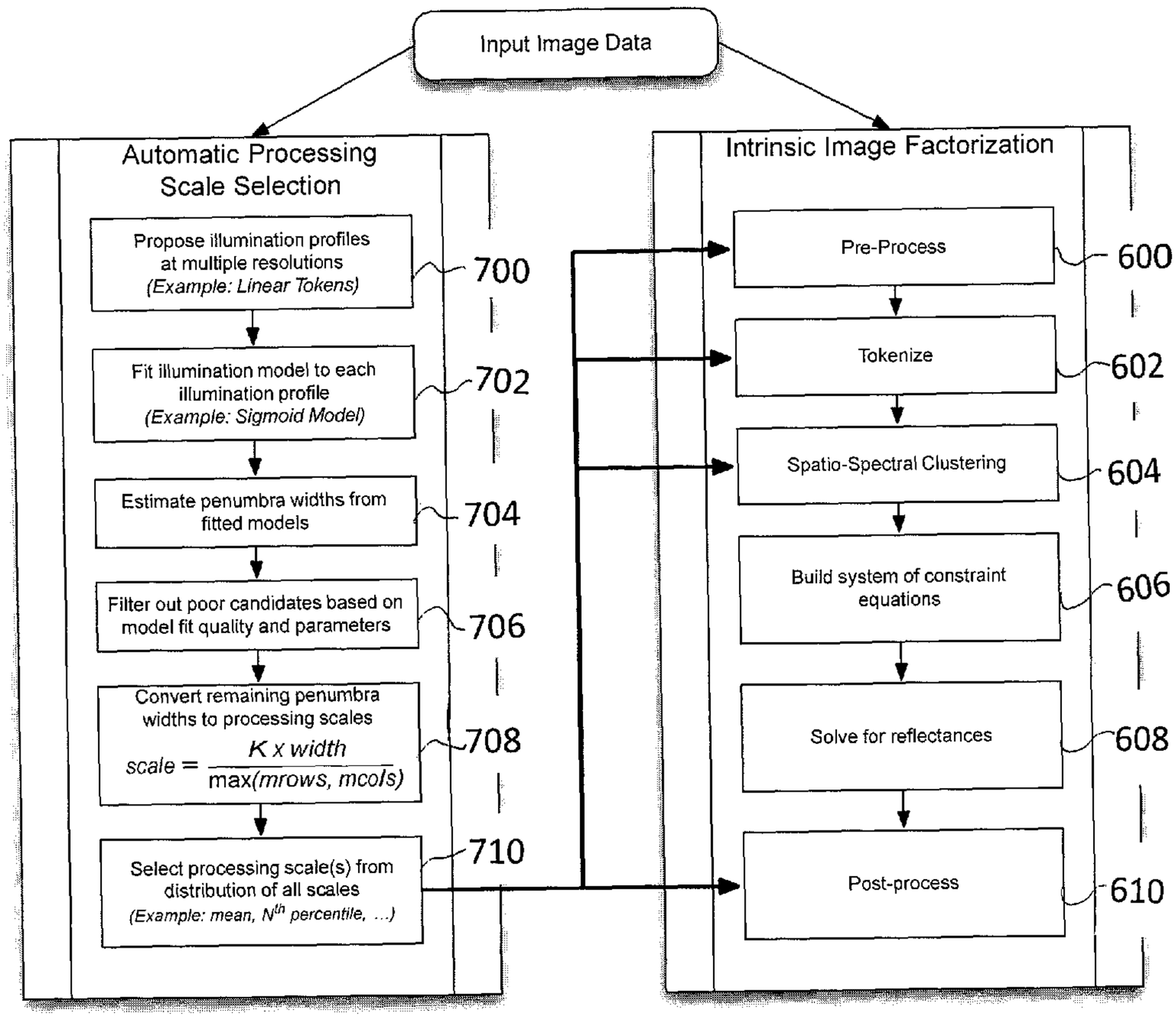

Input Image Data
Automatic Processing Scale Selection
Propose illumination profiles at multiple resolutions (Example: Linear Tokens)
700
Fit illumination model to each illumination profile (Example: Sigmoid Model)
702
Estimate penumbra widths from fitted models
704
Filter out poor candidates based on model fit quality and parameters
706
Convert remaining penumbra widths to processing scales
scale = K x width / max(mrows, mcols)
708
Select processing scale(s) from distribution of all scales
(Example: mean, Nth percentile, ...)
710
Intrinsic Image Factorization
Pre-Process
600
Tokenize
602
Spatio-Spectral Clustering
604
Build system of constraint equations
606
Solve for reflectances
608
Post-process
610

Fig. 19

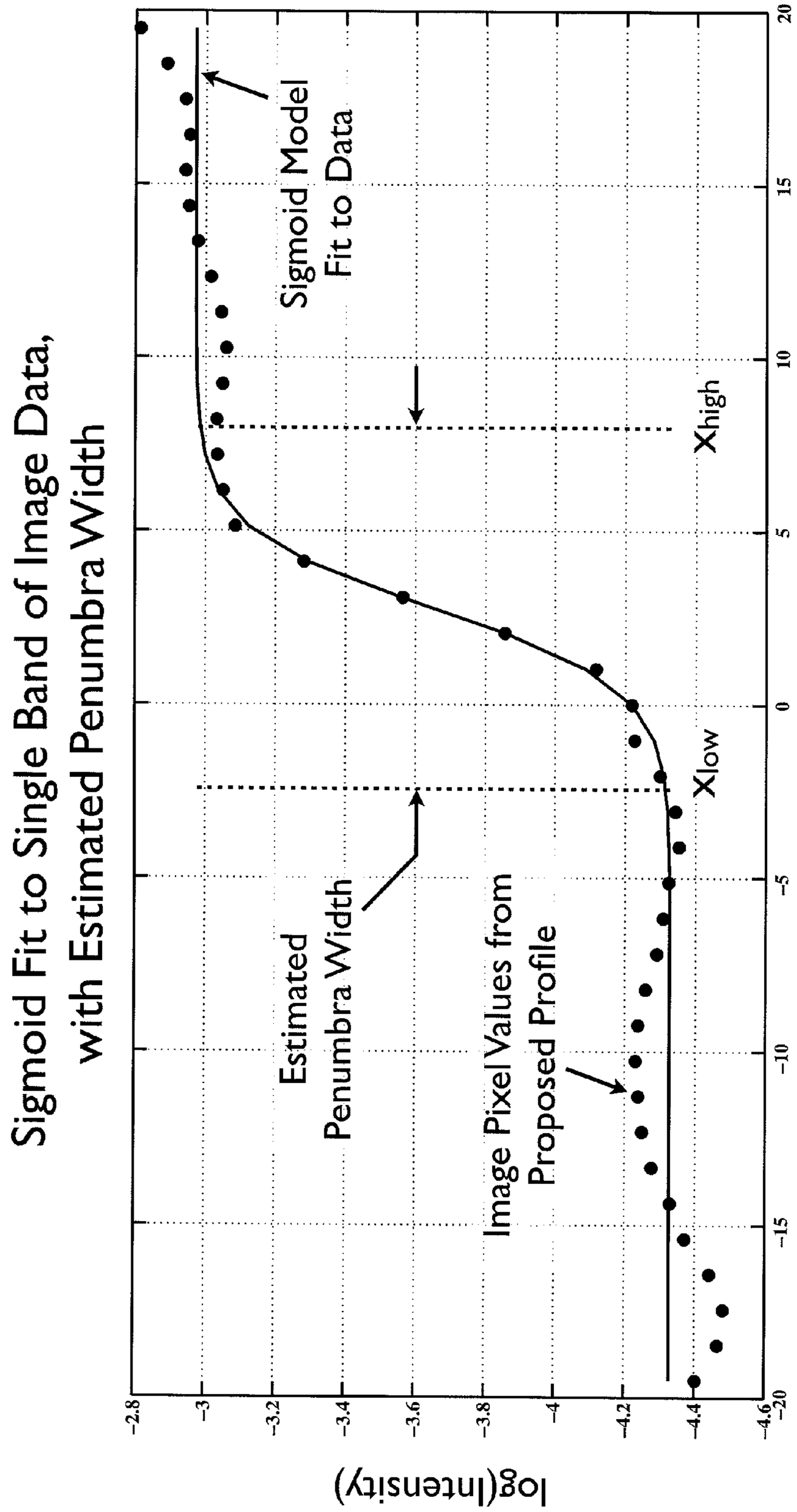

Sigmoid Fit to Single Band of Image Data, with Estimated Penumbra Width
Sigmoid Model Fit to Data
Estimated Penumbra Width
Image Pixel Values from Profile
Proposed Profile
Xlow
Xhigh
log(Intensity)
Distance from Image Edge (pixels)
-2.8
-3
-3.2
-3.4
-3.6
-3.8
-4
-4.2
-4.4
-4.6
20
15
10
5
0
-5
-10
-15
-20

Fig. 20

AUTOMATIC PROCESSING SCALE ESTIMATION FOR USE IN AN IMAGE PROCESS

BACKGROUND OF THE INVENTION

Many significant and commercially important uses of modern computer technology relate to images. These include image processing, image analysis and computer vision applications. In computer vision applications, such as, for example, object recognition and optical character recognition, it has been found that a separation of illumination and material aspects of an image can significantly improve the accuracy of computer performance. Significant pioneer inventions related to the illumination and material aspects of an image are disclosed in U.S. Pat. No. 7,873,219 to Richard Mark Friedhoff, entitled Differentiation Of Illumination And Reflection Boundaries and U.S. Pat. No. 7,672,530 to Richard Mark Friedhoff et al., entitled Method And System For Identifying Illumination Flux In An Image (hereinafter the Friedhoff Patents).

SUMMARY OF THE INVENTION

The present invention provides an improvement and enhancement to the fundamental teachings of the Friedhoff Patents, and includes a method and system comprising image techniques that accurately and correctly generate intrinsic images, including an automatic estimation of a processing scale for use in image processing techniques.

In a first exemplary embodiment of the present invention, an automated, computerized method is provided for processing an image. According to a feature of the present invention, the method comprises the steps of providing an image file depicting an image, in a computer memory, calculating processing scale parameter information as a function of width dimension information for penumbrae depicted in the image; and generating intrinsic illumination and material reflectance images corresponding to the image using the processing scale parameter information.

In a second exemplary embodiment of the present invention, a computer program product, disposed on a computer readable media is provided. The computer program product includes computer executable process steps operable to control a computer to: provide an image file depicting an image, in a computer memory, calculate processing scale parameter information as a function of width dimension information for penumbrae depicted in the image, and generate intrinsic illumination and material reflectance images corresponding to the image using the processing scale parameter information.

In accordance with yet further embodiments of the present invention, computer systems are provided, which include one or more computers configured (e.g., programmed) to perform the methods described above. In accordance with other embodiments of the present invention, non-transitory computer readable media are provided which have stored thereon computer executable process steps operable to control a computer(s) to implement the embodiments described above. The present invention contemplates a computer readable media as any product that embodies information usable in a computer to execute the methods of the present invention, including instructions implemented as a hardware circuit, for example, as in an integrated circuit chip. The automated, computerized methods can be performed by a digital computer, analog computer, optical sensor, state machine, sequencer, integrated chip or any device or apparatus that can be designed or programmed to carry out the steps of the methods of the present invention.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a block diagram of a computer system arranged and configured to perform operations related to images.

FIG. **2** shows an n×m pixel array image file for an image stored in the computer system of FIG. **1**.

FIG. **3***a* is a flow chart for identifying Type C token regions in the image file of FIG. **2**, according to a feature of the present invention.

FIG. **3***b* is an original image used as an example in the identification of Type C tokens.

FIG. **3***c* shows Type C token regions in the image of FIG. **3***b*.

FIG. **3***d* shows Type B tokens, generated from the Type C tokens of FIG. **3***c*, according to a feature of the present invention.

FIG. **4** is a flow chart for a routine to test Type C tokens identified by the routine of the flow chart of FIG. **3***a*, according to a feature of the present invention.

FIG. **5** is a graphic representation of a log color space chromaticity plane according to a feature of the present invention.

FIG. **6** is a flow chart for determining a list of colors depicted in an input image.

FIG. **7** is a flow chart for determining an orientation for a log chromaticity space.

FIG. **8** is a flow chart for determining log chromaticity coordinates for the colors of an input image, as determined through execution of the routine of FIG. **6**.

FIG. **9** is a flow chart for augmenting the log chromaticity coordinates, as determined through execution of the routine of FIG. **8**.

FIG. **10** is a flow chart for clustering the log chromaticity coordinates, according to a feature of the present invention.

FIG. **10***a* is an illustration of a grid for a spatial hash, according to a feature of the present invention.

FIG. **11** is a flow chart for assigning the log chromaticity coordinates to clusters determined through execution of the routine of FIG. **10**.

FIG. **12** is a flow chart for detecting regions of uniform reflectance based on the log chromaticity clustering.

FIG. **13** is a representation of an [A][x]=[b] matrix relationship used to identify and separate illumination and material aspects of an image, according to a same-material constraint, for generation of intrinsic images.

FIG. **14** illustrates intrinsic images including an illumination image and a material image corresponding to the original image of FIG. **3***b*.

FIG. **15** is a flow chart for an edge preserving blur post processing technique applied to the intrinsic images illustrated in FIG. **14**, according to a feature of the present invention.

FIG. **16** is a flow chart for an artifact reduction post processing technique applied to the intrinsic images illustrated in FIG. **14**, according to a feature of the present invention.

FIG. **17** is a flow chart for a BIDR model enforcement post processing technique applied to the intrinsic images illustrated in FIG. **14**, according to a feature of the present invention.

FIG. **18** is a graph in RGB color space showing colors for a material, from a fully shaded color value to a fully lit color value, as predicted by a bi-illuminant dichromatic reflection model.

FIG. **19** is a flow chart for an automatic processing scale estimation, according to a feature of the present invention.

FIG. **20** shows a graph for a sigmoid model used to calculate a penumbra width, for use in the automatic processing scale estimation illustrated in the flow chart of FIG. **19**.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

Referring now to the drawings, and initially to FIG. **1**, there is shown a block diagram of a computer system **10** arranged and configured to perform operations related to images. A CPU **12** is coupled to a device such as, for example, a digital camera **14** via, for example, a USB port. The digital camera **14** operates to download images stored locally on the camera **14**, to the CPU **12**. The CPU **12** stores the downloaded images in a memory **16** as image files **18**. The image files **18** can be accessed by the CPU **12** for display on a monitor **20**, or for print out on a printer **22**.

Alternatively, the CPU **12** can be implemented as a microprocessor embedded in a device such as, for example, the digital camera **14** or a robot. The CPU **12** can also be equipped with a real time operating system for real time operations related to images, in connection with, for example, a robotic operation or an interactive operation with a user.

As shown in FIG. **2**, each image file **18** comprises an n×m pixel array. Each pixel, p, is a picture element corresponding to a discrete portion of the overall image. All of the pixels together define the image represented by the image file **18**. Each pixel comprises a digital value corresponding to a set of color bands, for example, red, green and blue color components (RGB) of the picture element. The present invention is applicable to any multi-band image, where each band corresponds to a piece of the electro-magnetic spectrum. The pixel array includes n rows of m columns each, starting with the pixel p(1,1) and ending with the pixel p(n, m). When displaying or printing an image, the CPU **12** retrieves the corresponding image file **18** from the memory **16**, and operates the monitor **20** or printer **22**, as the case may be, as a function of the digital values of the pixels in the image file **18**, as is generally known.

In an image operation, the CPU **12** operates to analyze the RGB values of the pixels of a stored image file **18** to achieve various objectives, such as, for example, to identify regions of an image that correspond to a single material depicted in a scene recorded in the image file **18**. A fundamental observation underlying a basic discovery of the present invention, is that an image comprises two components, material and illumination. All changes in an image are caused by one or the other of these components. A method for detecting of one of these components, for example, material, provides a mechanism for distinguishing material or object geometry, such as object edges, from illumination and shadow boundaries.

Such a mechanism enables techniques that can be used to generate intrinsic images. The intrinsic images correspond to an original image, for example, an image depicted in an input image file **18**. The intrinsic images include, for example, an illumination image, to capture the intensity and color of light incident upon each point on the surfaces depicted in the image, and a material reflectance image, to capture reflectance properties of surfaces depicted in the image (the percentage of each wavelength of light a surface reflects). The separation of illumination from material in the intrinsic images provides the CPU **12** with images optimized for more effective and accurate further processing.

Pursuant to a feature of the present invention, processing is performed at a token level. A token is a connected region of an image wherein the pixels of the region are related to one another in a manner relevant to identification of image features and characteristics such as an identification of materials and illumination. The pixels of a token can be related in terms of either homogeneous factors, such as, for example, close correlation of color among the pixels, or inhomogeneous factors, such as, for example, differing color values related geometrically in a color space such as RGB space, commonly referred to as a texture. The present invention utilizes spatio-spectral information relevant to contiguous pixels of an image depicted in an image file **18** to identify token regions. The spatio-spectral information includes spectral relationships among contiguous pixels, in terms of color bands, for example the RGB values of the pixels, and the spatial extent of the pixel spectral characteristics relevant to a single material.

According to one exemplary embodiment of the present invention, tokens are each classified as either a Type A token, a Type B token or a Type C token. A Type A token is a connected image region comprising contiguous pixels that represent the largest possible region of the image encompassing a single material in the scene (uniform reflectance). A Type B token is a connected image region comprising contiguous pixels that represent a region of the image encompassing a single material in the scene, though not necessarily the maximal region of uniform reflectance corresponding to that material. A Type B token can also be defined as a collection of one or more image regions or pixels, all of which have the same reflectance (material color) though not necessarily all pixels which correspond to that material color. A Type C token comprises a connected image region of similar image properties among the contiguous pixels of the token, where similarity is defined with respect to a noise model for the imaging system used to record the image.

Referring now to FIG. **3***a*, there is shown a flow chart for identifying Type C token regions in the scene depicted in the image file **18** of FIG. **2**, according to a feature of the present invention. Type C tokens can be readily identified in an image, utilizing the steps of FIG. **3***a*, and then analyzed and processed to construct Type B tokens, according to a feature of the present invention.

A 1^{st} order uniform, homogeneous Type C token comprises a single robust color measurement among contiguous pixels of the image. At the start of the identification routine, the CPU **12** sets up a region map in memory. In step **100**, the CPU **12** clears the region map and assigns a region ID, which is initially set at 1. An iteration for the routine, corresponding to a pixel number, is set at i=0, and a number for an N×N pixel array, for use as a seed to determine the token, is set an initial value, $N=N_{start}$. N_{start} can be any integer >0, for example it can be set at set at 11 or 15 pixels.

At step **102**, a seed test is begun. The CPU **12** selects a first pixel, i=1, pixel (1, 1) for example (see FIG. **2**), the pixel at the upper left corner of a first N×N sample of the image file **18**. The pixel is then tested in decision block **104** to determine if the selected pixel is part of a good seed. The test can comprise a comparison of the color value of the selected pixel to the color values of a preselected number of its neighboring pixels as the seed, for example, the N×N array. The color values comparison can be with respect to multiple color band values (RGB in our example) of the pixel. If the comparison does not result in approximately equal values (within the noise levels of the recording device) for the pixels in the seed, the CPU **12** increments the value of i (step **106**), for example, i=2, pixel (1, 2), for a next N×N seed sample, and then tests to determine if $i=i_{max}$ (decision block **108**).

If the pixel value is at i_{max}, a value selected as a threshold for deciding to reduce the seed size for improved results, the seed size, N, is reduced (step **110**), for example, from N=15 to N=12. In an exemplary embodiment of the present invention, i_{max} can be set at a number of pixels in an image ending at pixel (n, m), as shown in FIG. **2**. In this manner, the routine of FIG. **3***a* parses the entire image at a first value of N before repeating the routine for a reduced value of N.

After reduction of the seed size, the routine returns to step **102**, and continues to test for token seeds. An N_{stop} value (for example, N=2) is also checked in step **110** to determine if the analysis is complete. If the value of N is at N_{stop}, the CPU **12** has completed a survey of the image pixel arrays and exits the routine.

If the value of i is less than i_{max}, and N is greater than N_{stop}, the routine returns to step **102**, and continues to test for token seeds.

When a good seed (an N×N array with approximately equal pixel values) is found (block **104**), the token is grown from the seed. In step **112**, the CPU **12** pushes the pixels from the seed onto a queue. All of the pixels in the queue are marked with the current region ID in the region map. The CPU **12** then inquires as to whether the queue is empty (decision block **114**). If the queue is not empty, the routine proceeds to step **116**.

In step **116**, the CPU **12** pops the front pixel off the queue and proceeds to step **118**. In step **118**, the CPU **12** marks "good' neighbors around the subject pixel, that is neighbors approximately equal in color value to the subject pixel, with the current region ID. All of the marked good neighbors are placed in the region map and also pushed onto the queue. The CPU **12** then returns to the decision block **114**. The routine of steps **114**, **116**, **118** is repeated until the queue is empty. At that time, all of the pixels forming a token in the current region will have been identified and marked in the region map as a Type C token.

When the queue is empty, the CPU **12** proceeds to step **120**. At step **120**, the CPU **12** increments the region ID for use with identification of a next token. The CPU **12** then returns to step **106** to repeat the routine in respect of the new current token region.

Upon arrival at $N=N_{stop}$, step **110** of the flow chart of FIG. **3***a*, or completion of a region map that coincides with the image, the routine will have completed the token building task. FIG. **3***b* is an original image used as an example in the identification of tokens. The image shows areas of the color blue and the blue in shadow, and of the color teal and the teal in shadow. FIG. **3***c* shows token regions corresponding to the region map, for example, as identified through execution of the routine of FIG. **3***a* (Type C tokens), in respect to the image of FIG. **3***b*. The token regions are color coded to illustrate the token makeup of the image of FIG. **3***b*, including penumbra regions between the full color blue and teal areas of the image and the shadow of the colored areas.

While each Type C token comprises a region of the image having a single robust color measurement among contiguous pixels of the image, the token may grow across material boundaries. Typically, different materials connect together in one Type C token via a neck region often located on shadow boundaries or in areas with varying illumination crossing different materials with similar hue but different intensities. A neck pixel can be identified by examining characteristics of adjacent pixels. When a pixel has two contiguous pixels on opposite sides that are not within the corresponding token, and two contiguous pixels on opposite sides that are within the corresponding token, the pixel is defined as a neck pixel.

FIG. **4** shows a flow chart for a neck test for Type C tokens. In step **122**, the CPU **12** examines each pixel of an identified token to determine whether any of the pixels under examination forms a neck. The routine of FIG. **4** can be executed as a subroutine directly after a particular token is identified during execution of the routine of FIG. **3***a*. All pixels identified as a neck are marked as "ungrowable." In decision block **124**, the CPU **12** determines if any of the pixels were marked.

If no, the CPU **12** exits the routine of FIG. **4** and returns to the routine of FIG. **3***a* (step **126**).

If yes, the CPU **12** proceeds to step **128** and operates to regrow the token from a seed location selected from among the unmarked pixels of the current token, as per the routine of FIG. **3***a*, without changing the counts for seed size and region ID. During the regrowth process, the CPU **12** does not include any pixel previously marked as ungrowable. After the token is regrown, the previously marked pixels are unmarked so that other tokens may grow into them.

Subsequent to the regrowth of the token without the previously marked pixels, the CPU **12** returns to step **122** to test the newly regrown token. Neck testing identifies Type C tokens that cross material boundaries, and regrows the identified tokens to provide single material Type C tokens suitable for use in creating Type B tokens.

FIG. **3***d* shows Type B tokens generated from the Type C tokens of FIG. **3***c*, according to a feature of the present invention. The present invention provides a novel exemplary technique using log chromaticity clustering, for constructing Type B tokens for an image file **18**. Log chromaticity is a technique for developing an illumination invariant chromaticity space.

A method and system for separating illumination and reflectance using a log chromaticity representation is disclosed in U.S. Pat. No. 7,596,266, which is hereby expressly incorporated by reference. The techniques taught in U.S. Pat. No. 7,596,266 can be used to provide illumination invariant log chromaticity representation values for each color of an image, for example, as represented by Type C tokens. Logarithmic values of the color band values of the image pixels are plotted on a log-color space graph. The logarithmic values are then projected to a log-chromaticity projection plane oriented as a function of a bi-illuminant dichromatic reflection model (BIDR model), to provide a log chromaticity value for each pixel, as taught in U.S. Pat. No. 7,596,266. The BIDR Model predicts that differing color measurement values fall within a cylinder in RGB space, from a dark end (in shadow) to a bright end (lit end), along a positive slope, when the color change is due to an illumination change forming a shadow over a single material of a scene depicted in the image.

FIG. **5** is a graphic representation of a log color space, bi-illuminant chromaticity plane according to a feature of the invention disclosed in U.S. Pat. No. 7,596,266. The alignment of the chromaticity plane is determined by a vector N, normal to the chromaticity plane, and defined as $N=\log(Bright_{vector})-\log(Dark_{vector})=\log(1+1/S_{vector})$. The co-ordinates of the plane, u, v can be defined by a projection of the green axis onto the chromaticity plane as the u axis, and the cross product of u and N being defined as the v axis. In our example, each log value for the materials A, B, C is projected onto the chromaticity plane, and will therefore have a corresponding u, v co-ordinate value in the plane that is a chromaticity value, as shown in FIG. **5**.

Thus, according to the technique disclosed in U.S. Pat. No. 7,596,266, the RGB values of each pixel in an image file **18** can be mapped by the CPU **12** from the image file value p(n, m, R, G, B) to a log value, then, through a projection to the chromaticity plane, to the corresponding u, v value, as shown

in FIG. **5**. Each pixel p(n, m, R, G, B) in the image file **18** is then replaced by the CPU **12** by a two dimensional chromaticity value: p(n, m, u, v), to provide a chromaticity representation of the original RGB image. In general, for an N band image, the N color values are replaced by N−1 chromaticity values. The chromaticity representation is a truly accurate illumination invariant representation because the BIDR model upon which the representation is based, accurately and correctly represents the illumination flux that caused the original image.

According to the invention disclosed and claimed in related application Ser. No. 12/927,244, filed Nov. 10, 2010, entitled System and Method for Identifying Complex Tokens in an Image (expressly incorporated by reference herein and hereinafter referred to as "related invention"), log chromaticity values are calculated for each color depicted in an image file **18** input to the CPU **12** for identification of regions of the uniform reflectance (Type B tokens). For example, each pixel of a Type C token will be of approximately the same color value, for example, in terms of RGB values, as all the other constituent pixels of the same Type C token, within the noise level of the equipment used to record the image. Thus, an average of the color values for the constituent pixels of each particular Type C token can be used to represent the color value for the respective Type C token in the log chromaticity analysis.

FIG. **6** is a flow chart for determining a list of colors depicted in an input image, for example, an image file **18**. In step **200**, an input image file **18** is input to the CPU **12** for processing. In steps **202** and **204**, the CPU **12** determines the colors depicted in the input image file **18**. In step **202**, the CPU **12** calculates an average color for each Type C token determined by the CPU **12** through execution of the routine of FIG. **3***a*, as described above, for a list of colors. The CPU **12** can be operated to optionally require a minimum token size, in terms of the number of constituent pixels of the token, or a minimum seed size (the N×N array) used to determine Type C tokens according to the routine of FIG. **3***a*, for the analysis. The minimum size requirements are implemented to assure that color measurements in the list of colors for the image are an accurate depiction of color in a scene depicted in the input image, and not an artifact of blend pixels.

Blend pixels are pixels between two differently colored regions of an image. If the colors between the two regions are plotted in RGB space, there is a linear transition between the colors, with each blend pixel, moving from one region to the next, being a weighted average of the colors of the two regions. Thus, each blend pixel does not represent a true color of the image. If blend pixels are present, relatively small Type C tokens, consisting of blend pixels, can be identified for areas of an image between two differently colored regions. By requiring a size minimum, the CPU **12** can eliminate tokens consisting of blend pixel from the analysis.

In step **204**, the CPU **12** can alternatively collect colors at the pixel level, that is, the RGB values of the pixels of the input image file **18**, as shown in FIG. **2**. The CPU **12** can be operated to optionally require each pixel of the image file **18** used in the analysis to have a minimum stability or local standard deviation via a filter output, for a more accurate list of colors. For example, second derivative energy can be used to indicate the stability of pixels of an image.

In this approach, the CPU **12** calculates a second derivative at each pixel, or a subset of pixels disbursed across the image to cover all illumination conditions of the image depicted in an input image file **18**, using a Difference of Gaussians, Laplacian of Gaussian, or similar filter. The second derivative energy for each pixel examined can then be calculated by the CPU **12** as the average of the absolute value of the second derivative in each color band (or the absolute value of the single value in a grayscale image), the sum of squares of the values of the second derivatives in each color band (or the square of the single value in a grayscale image), the maximum squared second derivative value across the color bands (or the square of the single value in a grayscale image), or any similar method. Upon the calculation of the second derivative energy for each of the pixels, the CPU **12** analyzes the energy values of the pixels. There is an inverse relationship between second derivative energy and pixel stability, the higher the energy, the less stable the corresponding pixel.

In step **206**, the CPU **12** outputs a list or lists of color (after executing one or both of steps **202** and/or **204**). According to a feature of the related invention, all of the further processing can be executed using the list from either step **202** or **204**, or vary the list used (one or the other of the lists from steps **202** or **204**) at each subsequent step.

FIG. **7** is a flow chart for determining an orientation for a log chromaticity representation, according to a feature of the related invention. For example, the CPU **12** determines an orientation for the normal N, for a log chromaticity plane, as shown in FIG. **5**. In step **210**, the CPU **12** receives a list of colors for an input file **18**, such as a list output in step **206** of the routine of FIG. **6**. In step **212**, the CPU **12** determines an orientation for a log chromaticity space.

As taught in U.S. Pat. No. 7,596,266, and as noted above, orientation of the chromaticity plane is represented by N, N being a vector normal to the chromaticity representation, for example, the chromaticity plane of FIG. **5**. The orientation is estimated by the CPU **12** thorough execution of any one of several techniques. For example, the CPU **12** can determine estimates based upon entropy minimization, manual selection of lit/shadowed regions of a same material by a user or the use of a characteristic spectral ratio (which corresponds to the orientation N) for an image of an input image file **18**, as fully disclosed in U.S. Pat. No. 7,596,266.

For a higher dimensional set of colors, for example, an RYGB space (red, yellow, green, blue), the log chromaticity normal, N, defines a sub-space with one less dimension than the input space. Thus, in the four dimensional RYGB space, the normal N defines a three dimensional log chromaticity space. When the four dimensional RYGB values are projected into the three dimensional log chromaticity space, the projected values within the log chromaticity space are unaffected by illumination variation.

In step **214**, the CPU **12** outputs an orientation for the normal N. As illustrated in the example of FIG. **5**, the normal N defines an orientation for a u, v plane in a three dimensional RGB space.

FIG. **8** is a flow chart for determining log chromaticity coordinates for the colors of an input image, as identified in steps **202** or **204** of the routine of FIG. **6**. In step **220**, a list of colors is input to the CPU **12**. The list of colors can comprise either the list generated through execution of step **202** of the routine of FIG. **6**, or the list generated through execution of step **204**. In step **222**, the log chromaticity orientation for the normal, N, determined through execution of the routine of FIG. **7**, is also input to the CPU **12**.

In step **224**, the CPU **12** operates to calculate a log value for each color in the list of colors and plots the log values in a three dimensional log space at respective (log R, log G, log B) coordinates, as illustrated in FIG. **5**. Materials A, B and C denote log values for specific colors from the list of colors input to the CPU **12** in step **220**. A log chromaticity plane is also calculated by the CPU **12**, in the three dimensional log space, with u, v coordinates and an orientation set by N, input

to the CPU **12** in step **222**. Each u, v coordinate in the log chromaticity plane can also be designated by a corresponding (log R, log G, log B) coordinate in the three dimensional log space.

According to a feature of the related invention, the CPU **12** then projects the log values for the colors A, B and C onto the log chromaticity plane to determine a u, v log chromaticity coordinate for each color. Each u, v log chromaticity coordinate can be expressed by the corresponding (log R, log G, log B) coordinate in the three dimensional log space. The CPU **12** outputs a list of the log chromaticity coordinates in step **226**. The list cross-references each color to a u, v log chromaticity coordinate and to the pixels (or a Type C tokens) having the respective color (depending upon the list of colors used in the analysis (either step **202**(tokens) or **204** (pixels))).

FIG. **9** is a flow chart for optionally augmenting the log chromaticity coordinates for pixels or Type C tokens with extra dimensions, according to a feature of the related invention. In step **230**, the list of log chromaticity coordinates, determined for the colors of the input image through execution of the routine of FIG. **8**, is input to the CPU **12**. In step **232**, the CPU **12** accesses the input image file **18**, for use in the augmentation.

In step **234**, the CPU **12** optionally operates to augment each log chromaticity coordinate with a tone mapping intensity for each corresponding pixel (or Type C token). The tone mapping intensity is determined using any known tone mapping technique. An augmentation with tone mapping intensity information provides a basis for clustering pixels or tokens that are grouped according to both similar log chromaticity coordinates and similar tone mapping intensities. This improves the accuracy of a clustering step.

In step **236**, the CPU **12** optionally operates to augment each log chromaticity coordinate with x, y coordinates for the corresponding pixel (or an average of the x, y coordinates for the constituent pixels of a Type C token) (see FIG. **2** showing a P (1,1) to P (N, M) pixel arrangement). Thus, a clustering step with x, y coordinate information will provide groups in a spatially limited arrangement, when that characteristic is desired.

In each of steps **234** and **236**, the augmented information can, in each case, be weighted by a factor w_1 and w_2, w_3 respectively, to specify the relative importance and scale of the different dimensions in the augmented coordinates. The weight factors w_1 and w_2, w_3 are user-specified. Accordingly, the (log R, log G, log B) coordinates for a pixel or Type C token is augmented to (log R, log G, log B, $T*w_1$, $x*w_2$, $y*w_3$) where T, x and y are the tone mapped intensity, the x coordinate and the y coordinate, respectively.

In step **238**, the CPU **12** outputs a list of the augmented coordinates. The augmented log chromaticity coordinates provide accurate illumination invariant representations of the pixels, or for a specified regional arrangement of an input image, such as, for example, Type C tokens. According to a feature of the related invention and the present invention, the illumination invariant characteristic of the log chromaticity coordinates is relied upon as a basis to identify regions of an image of a single material or reflectance, such as, for example, Type B tokens.

FIG. **10** is a flow chart for clustering the log chromaticity coordinates, according to a feature of the present invention. In step **240**, the list of augmented log chromaticity coordinates is input the CPU **12**. In step **242**, the CPU **12** operates to cluster the log chromaticity coordinates. According to the teachings of the related invention, the clustering step can be implemented via, for example, a known k-means clustering. Any known clustering technique can be used to cluster the log chromaticity coordinates to determine groups of similar log chromaticity coordinate values, according to the related invention. According to the teachings of each of the related invention and the present invention, the CPU **12** correlates each log chromaticity coordinate to the group to which the respective coordinate belongs.

According to a feature of the present invention, the clustering step **242** is implemented as a function of an index of the type used in database management, for example, a hash index, a spatial hash index, b-trees or any other known index commonly used in a database management system. By implementing the clustering step **242** as a function of an index, the number of comparisons required to identify a cluster group for each pixel or token of an image is minimized. Accordingly, the clustering step can be executed by the CPU **12** in a minimum amount of time, to expedite the entire image process.

FIG. **10***a* is an illustration of a grid for a spatial hash, according to a feature of an exemplary embodiment of the present invention. As shown in FIG. **10***a*, a spatial hash divides an image being processed into a grid of buckets, each bucket being dimensioned to be spatialThresh×spatialThresh. The grid represents a histogram of the u,v log chromaticity values for the cluster groups. As each cluster is created, a reference to the cluster is placed in the appropriate bucket of the grid.

Each new pixel or token of the image being processed is placed in the grid, in the bucket it would occupy, as if the item (pixel or token) was a new group in the clustering process. The pixel or token is then examined relative to the clusters in, for example, a 3×3 grid of buckets surrounding the bucket occupied by the item being examined. The item is added to the cluster group within the 3×3 gird, for example, if the item is within a threshold for a clusterMean.

The CPU **12** also operates to calculate a center for each group identified in the clustering step. For example, the CPU **12** can determine a center for each group relative to a (log R, log G, log B, log T) space.

In step **244**, the CPU **12** outputs a list of the cluster group memberships for the log chromaticity coordinates (cross referenced to either the corresponding pixels or Type C tokens) and/or a list of cluster group centers.

Pursuant to a further feature of the present invention, the list of cluster group memberships can be augmented with a user input of image characteristics. For example, a user can specify pixels or regions of the image that are of the same material reflectance. The CPU **12** operates to overlay the user specified pixels or regions of same reflectance onto the clustering group membership information.

As noted above, in the execution of the clustering method, the CPU **12** can use the list of colors from either the list generated through execution of step **202** of the routine of FIG. **6**, or the list generated through execution of step **204**. In applying the identified cluster groups to an input image, the CPU **12** can be operated to use the same set of colors as used in the clustering method (one of the list of colors corresponding to step **202** or to the list of colors corresponding to step **204**), or apply a different set of colors (the other of the list of colors corresponding to step **202** or the list of colors corresponding to step **204**). If a different set of colors is used, the CPU **12** proceeds to execute the routine of FIG. **11**.

FIG. **11** is a flow chart for assigning the log chromaticity coordinates to clusters determined through execution of the routine of FIG. **10**, when a different list of colors is used after the identification of the cluster groups, according to a feature of the present invention. In step **250**, the CPU **12** once again executes the routine of FIG. **8**, this time in respect to the new

list of colors. For example, if the list of colors generated in step **202** (colors based upon Type C tokens) was used to identify the cluster groups, and the CPU **12** then operates to classify log chromaticity coordinates relative to cluster groups based upon the list of colors generated in step **204** (colors based upon pixels), step **250** of the routine of FIG. **11** is executed to determine the log chromaticity coordinates for the colors of the pixels in the input image file **18**.

In step **252**, the list of cluster centers is input to the CPU **12**. In step **254**, the CPU **12** operates to classify each of the log chromaticity coordinates identified in step **250**, according to the nearest cluster group center. In step **256**, the CPU **12** outputs a list of the cluster group memberships for the log chromaticity coordinates based upon the new list of colors, with a cross reference to either corresponding pixels or Type C tokens, depending upon the list of colors used in step **250** (the list of colors generated in step **202** or the list of colors generated in step **204**).

FIG. **12** is a flow chart for detecting regions of uniform reflectance based on the log chromaticity clustering according to a feature of the present invention. In step **260**, the input image file **18** is once again provided to the CPU **12**. In step **262**, one of the pixels or Type C tokens, depending upon the list of colors used in step **250**, is input to the CPU **12**. In step **264**, the cluster membership information, form either steps **244** or **256**, is input to the CPU **12**.

In step **266**, the CPU **12** operates to merge each of the pixels, or specified regions of an input image, such as, for example, Type C tokens, having a same cluster group membership into a single region of the image to represent a region of uniform reflectance (Type B token). The CPU **12** performs such a merge operation for all of the pixels or tokens, as the case may be, for the input image file **18**. In step **268**, the CPU **12** outputs a list of all regions of uniform reflectance (and also of similar tone mapping intensities and x, y coordinates, if the log chromaticity coordinates were augmented in steps **234** and/or **236**). It should be noted that each region of uniform reflectance (Type B token) determined according to the features of the present invention, potentially has significant illumination variation across the region.

U.S. Pat. No. 8,139,867 teaches a constraint/solver model for segregating illumination and material in an image, including an optimized solution based upon a same material constraint. A same material constraint, as taught in U.S. Pat. No. 8,139,867, utilizes Type C tokens and Type B tokens, as can be determined according to the teachings of the present invention. The constraining relationship is that all Type C tokens that are part of the same Type B token are constrained to be of the same material. This constraint enforces the definition of a Type B token, that is, a connected image region comprising contiguous pixels that represent a region of the image encompassing a single material in the scene, though not necessarily the maximal region corresponding to that material. Thus, all Type C tokens that lie within the same Type B token are by the definition imposed upon Type B tokens, of the same material, though not necessarily of the same illumination. The Type C tokens are therefore constrained to correspond to observed differences in appearance that are caused by varying illumination.

FIG. **13** is a representation of an [A][x]=[b] matrix relationship used to identify and separate illumination and material aspects of an image, according to a same-material constraint, as taught in U.S. Pat. No. 8,139,867. Based upon the basic equation I=ML (I=the recorded image value, as stored in an image file **18**, M=material reflectance, and L=illumination), log(I)=log(ML)=log(M)+log(L). This can be restated as i=m+l, wherein i represents log(I), m represents log(M) and l represents log(L). In the constraining relationship of a same material, in an example where three Type C tokens, a, b and c, (as shown in FIG. **13**) are within a region of single reflectance, as defined by a corresponding Type B token defined by a, b and c, then $m_a=m_b=m_c$. For the purpose of this example, the I value for each Type C token is the average color value for the recorded color values of the constituent pixels of the token. The a, b and c, Type C tokens of the example can correspond to the blue Type B token illustrated in FIG. **3***d*.

Since: $m_a=i_a-l_a$, $m_b=i_b-l_b$, and $m_c=i_c-l_c$, these mathematical relationships can be expressed, in a same material constraint, as $(1)l_a+(-1)l_b+(0)l_c=(i_a-i_b)$, $(1)l_a+(0)l_b+(-1)l_c=(i_a-i_c)$ and $(0)l_a+(1)l_b+(-1)l_c=(i_b-i_c)$.

Thus, in the matrix equation of FIG. **13**, the various values for the log(I) (i_a, i_b, i_c), in the [b] matrix, are known from the average recorded pixel color values for the constituent pixels of the adjacent Type C tokens a, b and c. The [A] matrix of 0's, 1's and −1's, is defined by the set of equations expressing the same material constraint, as described above. The number of rows in the [A] matrix, from top to bottom, corresponds to the number of actual constraints imposed on the tokens, in this case three, the same material constraint between the three adjacent Type C tokens a, b and c. The number of columns in the [A] matrix, from left to right, corresponds to the number of unknowns to be solved for, again, in this case, the three illumination values for the three tokens. Therefore, the values for the illumination components of each Type C token a, b and c, in the [x] matrix, can be solved for in the matrix equation, by the CPU **12**. It should be noted that each value is either a vector of three values corresponding to the color bands (such as red, green, and blue) of our example or can be a single value, such as in a grayscale image.

Once the illumination values are known, the material color can be calculated by the CPU **12** using the I=ML equation. Intrinsic illumination and material images can be now be generated for the region defined by tokens a, b and c, by replacing each pixel in the original image by the calculated illumination values and material values, respectively. An example of an illumination image and material image, corresponding to the original image shown in FIG. **3***b*, is illustrated in FIG. **14**.

Implementation of the constraint/solver model according to the techniques and teachings of U.S. Pat. No. 8,139,867, utilizing the Type C tokens and Type B tokens obtained via a log chromaticity clustering technique according to the present invention, provides a highly effective and efficient method for generating intrinsic images corresponding to an original input image. The intrinsic images can be used to enhance the accuracy and efficiency of image processing, image analysis and computer vision applications.

However, the intrinsic images generated from the performance of the exemplary embodiments of the present invention can include artifacts that distort the appearance of a scene depicted in the image being processed. The artifacts can be introduced through execution of the intrinsic image generations methods of the present invention, or through user modifications such as the user input of image characteristics discussed above. Accordingly, according to a feature of the present invention, various post processing techniques can be implemented to reduce the artifacts.

FIG. **15** is a flow chart for an edge preserving blur post processing technique applied to the intrinsic images illustrated in FIG. **14**, according to a feature of the present invention, to improve the quality of the illumination and material reflectance aspects depicted in the intrinsic images. In step **300**, the CPU **12** receives as an input an original image (an

image file **18**), and the corresponding intrinsic material reflectance and illumination images determined by the CPU **12** through solution of the matrix equation shown in FIG. **13**, as described above.

In step **302**, the CPU **12** operates to perform an edge-preserving blur of the illumination in the illumination image by applying an edge preserving smoothing filter. The edge preserving smoothing filter can be any one of the known filters such as, for example, a bilateral filter, a guided filter, a mean-shift filter, a median filter, anisotropic diffusion and so on. The filter can be applied one or more times to the illumination image. In an exemplary embodiment, a bilateral filter is applied to the illumination image twice. In addition, several different types of filters can be applied in succession, for example, a median filter followed by a bilateral filter.

In step **304**, the CPU **12** recalculates the intrinsic material reflectance image based upon the I=ML equation, and using the original image of the image file **18** and the illumination image, as modified in step **302**. In step **306**, the CPU **12** outputs intrinsic material reflectance and illumination images, as modified by the CPU **12** through execution of the routine of FIG. **15**.

A smoothing filter applied to the illumination image results in several improvements to the appearance of the intrinsic images when used in, for example, such applications as computer graphics. For example, in computer graphics, texture mapping is used to achieve certain special effects. Artists consider it desirable in the performance of texture mapping to have some fine scale texture form the illumination in the material reflectance image. By smoothing the illumination image, in step **302**, the fine scale texture is moved to the material reflectance image upon a recalculation of the material image in step **304**, as will be described below.

In addition, smoothing the illumination in step **302** places some of the shading illumination (illumination intensity variation due to curvature of a surface) back into the material reflectance image, giving the material image some expression of curvature. That results in an improved material depiction more suitable for artistic rendering in a computer graphics application.

Moreover, small reflectance variation sometimes erroneously ends up in the illumination image. The smoothing in step **302** forces the reflectance variation back into the material image.

FIG. **16** is a flow chart for an artifact reduction post processing technique applied to the intrinsic images illustrated in FIG. **14**, according to a feature of the present invention, to improve the quality of the illumination and material reflectance aspects depicted in the intrinsic images. In step **400**, the CPU **12** receives as an input an original image (an image file **18**), and the corresponding intrinsic material reflectance and illumination images determined by the CPU **12** through solution of the matrix equation shown in FIG. **13**, as described above. Optionally, the intrinsic images can be previously modified by the CPU **12** through execution of the routine of FIG. **15**.

In step **402**, the CPU **12** operates to calculate derivatives (the differences between adjacent pixels) for the pixels of each of the original image and the material reflectance image. Variations between adjacent pixels, in the horizontal and vertical directions, are caused by varying illumination and different materials in the scene depicted in the original image. When the CPU **12** operates to factor the original image into intrinsic illumination and material reflectance images, some of the variation ends up in the illumination image and some ends up in the material reflectance image. Ideally, all of the variation in the illumination image is attributable to varying illumination, and all of the variation in the material reflectance image is attributable to different materials.

Thus, by removing the illumination variation, variations in the material reflectance image should be strictly less than variations in the original image. However, inaccuracies in the process for generating the intrinsic images can result in new edges appearing in the material reflectance image.

In step **404**, the CPU **12** operates to identify the artifacts caused by the newly appearing edges by comparing the derivatives for the material reflectance image with the derivatives for the original image. The CPU **12** modifies the derivatives in the material reflectance image such that, for each derivative of the material reflectance image, the sign is preserved, but the magnitude is set at the minimum of the magnitude of the derivative in the original image and the material reflectance image. The modification can be expressed by the following equation:

```
derivativeReflectanceNew=min(abs(derivativeReflec-
    tanceOld),abs(derivativeOriginalimage))*sign
    (derivativeReflectanceOld)
```

In step **406**, the CPU integrates the modified derivatives to calculate a new material reflectance image. The new image is a material reflectance image without the newly appearing, artifact-causing edges. Any known technique can be implemented to perform the integration. For example, the CPU **12** can operate to perform numerical 2D integration by solving the 2D Poisson equation using discrete cosine transforms.

In step **408**, the CPU **12** recalculates the intrinsic illumination image based upon the I=ML equation, and using the original image of the image file **18** and the material reflectance image, as modified in steps **404** and **406**. In step **408**, the CPU **12** outputs intrinsic material reflectance and illumination images, as modified by the CPU **12** through execution of the routine of FIG. **16**.

FIG. **17** is a flow chart for a BIDR model enforcement post processing technique applied to the intrinsic images illustrated in FIG. **14**, according to a feature of the present invention, to improve the quality of the illumination and material reflectance aspects depicted in the intrinsic images.

As described above, the BIDR model predicts the correct color for a material, in a shadow penumbra, from full shadow to fully lit. As shown in FIG. **18**, according to the prediction of the BIDR model, colors for a material, for example, in an RGB color space, from a fully shaded color value to a fully lit color value, generally form a line in the color space. In full shadow, the material is illuminated by an ambient illuminant, while when fully lit, the material is illuminated by the ambient illuminant and the direct or incident illuminant present in the scene at the time the digital image of an image file **18** was recorded.

According to the BIDR model, the illumination values in an image also define a line extending from the color of the ambient illuminant to the color of the combined ambient and direct illuminants. In log color space, the illumination line predicted by the BIDR model corresponds to the normal, N of the log color space chromaticity plane illustrated in FIG. **5**.

Various inaccuracies in the generation of the illumination and material intrinsic images, as described above, can also result, for example, in illumination values in the generated intrinsic illumination image that diverge from the line for the illumination values predicted by the BIDR model. According to the present invention, the illumination line prediction of the BIDR model is used to correct such inaccuracies by modifying the illumination to be linear in log(RGB) space.

Referring once again to FIG. **17**, in step **500**, the CPU **12** receives as input a BIDR illumination orientation, corre-

sponding to the normal N illustrated in FIG. **5**. In the exemplary embodiment of the present invention, N is determined by the CPU **12** through execution of the routine of FIG. **7**, as described above. In that case, the N determined through execution of the routine of FIG. **7** is used in both the clustering process described above, and in the BIDR model enforcement post processing technique illustrated in FIG. **17**.

In the event the illumination and material reflectance images are generated via a method different from the log chromaticity clustering technique of the exemplary embodiment, the orientation N is determined by the CPU **12** in a separate step before the execution of the routine of FIG. **17**, through execution of the routine of FIG. **7**. When N is determined in a separate step, the CPU **12** can operate relative to either the original image or the illumination image. In addition, when the processing is based upon a user input, as described above, the user can make a selection from either the original image or the illumination image.

Moreover, in step **500**, the CPU **12** also receives as input an original image (an image file **18**), and the corresponding intrinsic material reflectance and illumination images determined by the CPU **12** through solution of the matrix equation shown in FIG. **13**, also as described above. Optionally, the intrinsic images can be previously modified by the CPU **12** through execution of the routine(s) of either one, or both FIGS. **15** and **16**.

In step **502**, the CPU **12** determines the full illumination color in the illumination image. The full illumination color (ambient+direct) can be the brightest color value depicted in the illumination image. However, the brightest value can be inaccurate due to noise in the image or other outliers. In a preferred exemplary embodiment of the present invention, a more accurate determination is made by finding all illumination color values in a preselected range of percentiles of the intensities, for example, the 87^{th} through 92^{nd} percentiles, and calculating an average of those values. The average is used as the full illumination color value. Such an approach provides a robust estimate of the bright end of the illumination variation in the intrinsic illumination image.

In step **504**, the CPU **12** operates to modify all of the pixels of the illumination image by projecting all of the illumination colors depicted by the pixels in the illumination image to the nearest point on a line having the orientation N (input to the CPU **12** in step **500**) and passing through the full illumination color determined in step **302**. Thus, the color of each pixel of the illumination image is modified to conform to the closest value required by the BIDR model prediction.

A special case exists for the pixels of the illumination image having an intensity that is greater than the full illumination color value, as calculated in step **502**. The special case can be handled by the CPU **12** according to a number of different methods. In a first method, the modification is completed as with all the other pixels, by projecting each high intensity pixel to the nearest value on the illumination line. In a second method, each high intensity pixel is replaced by a pixel set at the full illumination color value. According to a third method, each high intensity pixel is kept at the color value as in the original image.

An additional method is implemented by using a weighted average for each high intensity pixel, of values determined according to the first and third methods, or of values determined according to the second and third methods. The weights would favor values calculated according to either the first or second methods when the values are similar to high intensity pixels that are not significantly brighter than the full illumination color value calculated in step **502**. Values calculated via the third method are favored when values for high intensity pixels that are significantly brighter than the full illumination color value. Such a weighting scheme is useful when the I=ML equation for image characteristics is inaccurate, for example, in the presence of specular reflections.

Any known technique can be implemented to determine the relative weights for illumination values. In an exemplary embodiment of the present invention, a sigmoid function is constructed such that all the weight is on the value determined either according to the first or second methods, when the intensity of the high intensity pixel is at or near the full illumination color value, with a smooth transition to an equally weighted value, between a value determined either according to the first or second methods and a value determined according to the third method, as the intensity increases. That is followed by a further smooth transition to full weight on a value determined according to the third method, as the intensity increase significantly beyond the full illumination color value.

In step **506**, the CPU **12** recalculates the intrinsic material reflectance image based upon the I=ML equation, and using the original image of the image file **18** and the illumination image, as modified in step **504**. In step **508**, the CPU **12** outputs intrinsic material reflectance and illumination images modified to strictly adhere to the predictions of the BIDR model.

For best results, the above-described post processing techniques can be executed in a log(RGB) space. Also, the various techniques can be executed in the order described above. Once one or more of the post processing techniques have been executed, the final modified intrinsic images can be white balanced and/or scaled, as desired, and output by the CPU **12**.

A processing scale is a parameter relevant to each of the tokenization method, to identify Type C tokens, the log chromaticity clustering, and the post-processing techniques, as described above. The processing scale parameter is related to the width of shadow penumbrae appearing in an image being processed for generation of corresponding intrinsic illumination and material reflectance images. The shadow penumbrae each span an area of the image, each penumbra area depicting a transition from a fully illuminated region of the image, to an adjacent region in full shadow. An accurate estimation of the spatial distances spanned by the pixels of the penumbrae present in a scene depicted in the image, as represented by processing scale parameter information, facilitates a more accurate segregation or factorization of an image into the corresponding intrinsic images.

FIG. **19** is a flow chart for an automatic processing scale estimation technique, according to a feature of the present invention. The flow chart illustrates the automatic processing scale selection process of the exemplary embodiment of the present invention, in a flow chart section on the left side of the overall flow chart, and further illustrates a right side, high level flow chart section showing the image process to identify intrinsic images corresponding to an original image (intrinsic image factorization), as described in detail above. Flow chart lines between the left side and right side sections of the overall flow chart indicate the applications of the estimated processing scale(s), as determined in the automatic processing scale selection process, to the various steps of the intrinsic image factorization process. As shown in FIG. **19**, image data, for example, an image file **18**, is input to each of the automatic processing scale selection process and the intrinsic image factorization process.

As shown in the right side of FIG. **19**, the intrinsic image factorization of the present invention can include a pre-process step (step **600**), for example, a selective, initial blurring of the image to reduce the number of tokens to be processed

in the factorization, for a faster execution time. Steps **602** to **610** of the right side section of FIG. **19** correspond to the above-described method for generating intrinsic illumination and material reflectance images.

For example, in step **602**, the CPU **12** executes the routine of FIG. **3***a*, to identify the Type C tokens used in the generation of the intrinsic images. In step **604**, the CPU **12** executes the log-chromaticity clustering of the routines of FIGS. **6-12**, to identify regions of uniform reflectance. In step **606**, the CPU uses the regions of uniform reflectance to build the matrix equation illustrated in FIG. **13**. In step **608**, the CPU **12** solves the matrix equation to generate the intrinsic images shown in FIG. **14**. Finally, in step **610**, the CPU **12** executes the post-processing routines of FIGS. **15-17**.

According to a feature of the exemplary embodiment of the present invention, the CPU **12** operates to execute the automatic processing scale selection, shown in the left side section of FIG. **19**, prior to execution of the intrinsic image factorization, to calculate processing scale information. The processing scale information is then used for a more accurate execution of steps **600**, **602**, **604** and **610** of the image factorization.

In step **700** of the automatic processing scale selection, the CPU **12** operates to identify prospective illumination profiles through penumbrae, at multiple resolutions of the image being processed. Each illumination profile illustrates color transitions among and the spatial extent of contiguous pixels, from pixels in full shadow, through the pixels in the penumbra, to pixels at full illumination, for example, as shown in the illustration of FIG. **18**. The illumination profiles provide illumination profile information that can be used to determine width dimension information, for example, an estimate of the widths of the various penumbrae depicted in the image.

Generally, each illumination profile is selected so as to provide image data along lines orthogonal to illumination transitions depicted in the image, image data that adhere to a set of heuristics for expected illumination transitions through a shadow penumbra. For example, the pixels represented in each illumination profile have physically reasonable spectral ratios, and sufficiently bright and sufficiently dark color intensities at the ends of the respective profile, consistent with real world illumination transition conditions associated with a shadow penumbra.

In an exemplary embodiment of the present invention, step **700** is implemented by identifying linear tokens in the image being processed. A linear token is a nonhomogeneous token comprising a connected region of the image wherein adjacent pixels of the region have differing color measurement values that fall within a cylinder in RGB space, from a dark end (in shadow) to a bright end (lit end), along a positive slope. The cylinder configuration is predicted by the bi-illuminant dichromatic reflection model (BIDR model). As described above, the BIDR model predicts the correct color for a material, in a shadow penumbra, from full shadow to fully lit. Each linear token, therefore, provides a candidate image region that likely corresponds to a line passing through a penumbra depicted in the image.

U.S. Pat. No. 7,995,058 discloses a technique for analyzing pixels of an image to identify contiguous pixels forming linear tokens throughout the image. In step **700**, the CPU **12** is operated to execute the technique taught in U.S. Pat. No. 7,995,058, to identify a set of linear tokens in the image being processed, executing the technique once at each of several preselected resolutions of the image, for example, at the original resolution of the image, and several down-sampled versions of the image.

In step **702**, the CPU **12** is operated to fit an illumination model to each of the illumination profiles, for example, as represented by the linear tokens. For example, a 4-parameter sigmoid model is applied to each of the RGB bands of the pixels of each linear token identified by the CPU **12** in step **700**. The sigmoid can be determined using a known technique, such as the Levenberg-Marquardt method. FIG. **20** shows a graph illustrating a sigmoid model for one band of the pixels of an identified linear token, used to calculate a penumbra width.

According to a feature of the exemplary sigmoid embodiment of the present invention, the four parameters of the sigmoid model include xcen, the center of the sigmoid, relative to the distance from image edge position, as shown in FIG. **20**, s, slope (the rate of change measured by intensity vs distance from image edge), yscale, the difference, in intensity, between the flat bright and dark portions of the profile, and yshift, the vertical shift (in intensity) required to align the sigmoid model with the dark portion of the underlying pixel data.

In step **704**, the CPU **12** operates to estimate penumbrae widths, from lit to dark, as a function of the fitted sigmoid parameters. The length of each particular penumbra can be expressed relative to x positions, x_{low} and x_{high}, the positions at which the sigmoid model for the respective penumbra reaches the minimum and maximum values, respectively (as shown by the vertical dashed lines in the graph of FIG. **20**, the left vertical dashed line corresponds to the x_{low} position and the right vertical dashed line corresponds to the x_{high} position). The calculation of the penumbra width w for a particular penumbra is performed (based upon a determination of the positions within a fraction, p, of the minimum and maximum values), as follows:

$$y_{low}=\log((1-p)/p)$$

$$y_{high}=\log(p/(1-p)),$$

then

$$x_{low}=-y_{low}-x\text{cen}/s,$$

and

$$x_{high}-y_{high}-x\text{cen}/s,$$

with

$$w=|x_{high}-x_{low}|$$

wherein p is a given fraction to quantify the proximity of x_{low} and x_{high} to the sigmoid model. In the exemplary embodiment of the present invention, p is set at 0.01.

In step **706**, the CPU **12** operates to filter out illumination profiles that are deemed unlikely to correspond to an illumination transition of a shadow penumbra. The goal is to eliminate from further processing any of the candidate illumination profiles represented by, for example, the linear tokens, that do not reflect such an illumination transition. Step **706** is executed based upon information provided by the fitted sigmoid parameters. For example, a check of the signs of the slope parameters, s, of the sigmoid model of each of the RGB bands of a linear token can be made to verify that all of the bands indicate either an increase or decrease along the transition, as occurs in an illumination transition. If one of the bands increases while the other bands decrease, the corresponding linear token does not correspond to an illumination transition, and is removed from the process.

Further checks can include, for example, thresholds on the fit quality (e.g. in terms of RMS error) and verification that penumbra widths among the bands of an illumination profile agree with one another. The result of step **706** is a reduction of the number of candidate illumination profiles to include profiles each representing a high likelihood of corresponding to an illumination transition.

In step **708**, the CPU **12** operates to calculate a processing scale for each of the remaining candidate illumination profiles i, for example, as represented by the linear tokens, as a function of the penumbra widths w_i calculated in step **704**. In an exemplary embodiment of the present invention, each processing scale is calculated as a function that is proportional to the calculated width w_i to ensure that the processing scale represents the distance between pixels that are fully lit and pixels in full shadow. Accordingly, the processing scale calculation is adjusted by K, a constant of proportionality, to expand the distance between the x_{low} and x_{high} positions, to ensure that the analysis is relative to fully lit and fully shadowed regions of the image when performance depends upon the processing scale parameter.

Thus, each processing scale, proc_scale, is calculated, as follows:

$$\text{proc\_scale}_i = K * w_i / \max(N_{rows}, M_{cols})$$

wherein N_{rows}, M_{cols} correspond to the number of rows and columns of pixels in the image being processed, as shown, for example, in FIG. **2**. The N_{rows}, M_{cols} denominator is used to normalize the parameter quantity so as to be independent of the specific size of a particular image, and thus be comparable across images of all sizes.

From the set of processing scales, proc_scale, calculated by the CPU **12** in step **708**, the CPU **12** is operated to select one or more of the processing scales for use in the intrinsic image factorization shown in the right side section of the flow chart of FIG. **19** (step **710**). In one exemplary embodiment of the present invention, execution of step **710** is implemented such that a single processing scale is calculated from the average of the distribution of processing scales, as follows:

$$\text{proc\_scale} = 1/N_{profiles} \Sigma \text{ (from i=1 to } N_{profiles}) \text{proc\_scale},$$

wherein $N_{profiles}$ is the number of candidate illumination profiles i, from step **708**.

In other exemplary embodiments of the present invention, for implementation of step **710**, the CPU **12** specifies a percentile of the distribution of processing scales, for example, a median (50^{th} percentile) or the 90^{th} percentile, for use in the intrinsic image factorization, or determines a set of spatially-varying processing scales. For the set of spatially-varying processing scales, the spatial positions of the illumination profiles are considered to select representative processing scales at various locations within the image, according to local distributions of proposed scales, or by clustering, using, for example, a mean-shift or K-means clustering technique based upon spatial position and scale as dimensions for the clustering.

Upon completion of steps **700-710**, the CPU **12** uses the estimated processing scale(s) in the execution of steps **600**, **602**, **604** and **610** of the image factorization shown in the right side section of the flow chart of FIG. **19**, as noted above. In the pre-process of step **600**, for a selective, initial blurring of the image to reduce the number of tokens to be processed in the factorization, the processing scale is used to control the bandwidth of the blur filter kernel.

Relative to the tokenization of step **602**, the spatial positions of the tokens in the clustering of step **604** can be based upon the centroid position of each token. To avoid requiring a measure of spatial proximity in the clustering of step **604** that is more complex than simple Euclidean distance between centroid positions, the growth process in the tokenization can be implemented so as to limit maximum token size. The maximum token size is set such that the distance between a token and the neighboring tokens, based upon centroid distances, is assured to be small enough such that the respective token can potentially be clustered with the neighboring tokens based upon the spatial and spectral distances used in the clustering of step **604**. For example, a larger processing scale permits tokens to be grown to larger sizes, since the clustering algorithm can consider centroid positions that are further apart. Accordingly, maximum token size is set as a function of the processing scale.

As noted, the distance between the centroid positions of tokens is used as a dimension in the log chromaticity clustering of step **604**. The clustering is also based upon log chromaticity values. To make the combined dimensions of the centroid distance and chromaticity values, which have different units, numerically compatible, the spatial dimension is scaled as a function of the processing scale. Thus, the clustering can be implemented relative to a combined space with dimensions corresponding to chromaticity value and spatial position, to allow for a single clustering radius. The processing scale is used to adjust the requisite relative weight between the centroid distances and log chromaticity values such that a larger processing scale makes more spatially-separated centroid positions appear closer together (relative to the corresponding log chromaticity distance) for purposes of clustering.

During the post-processing phase of the intrinsic image factorization, a smoothing operator such as, for example, a bilateral filter, can optionally be applied to the illumination image (with a corresponding adjustment to the material reflectance image). This provides an adjustment to the smoothness of the illumination image, allowing control over how much detail appears in the final illumination vents material reflectance result. The spatial bandwidth is directly proportional to the processing scale parameter, such that a larger processing scale results in a more spatially smooth illumination field when a smoothing operator is used.

In the preceding specification, the invention has been described with reference to specific exemplary embodiments and examples thereof. It will, however, be evident that various modifications and changes may be made thereto without departing from the broader spirit and scope of the invention as set forth in the claims that follow. The specification and drawings are accordingly to be regarded in an illustrative manner rather than a restrictive sense.

What is claimed is:

1. An automated, computerized method for processing an image, comprising the steps of:

providing an image file depicting the image, in a computer memory;

calculating processing scale parameter information as a function of width dimension information for penumbrae depicted in the image; and

generating, from the image, intrinsic illumination and material reflectance images corresponding to the image using the processing scale parameter information, wherein the intrinsic illumination image represents intensity and color of light incident upon each point on surfaces depicted in the image and the intrinsic material reflectance image represents reflectance properties of surfaces depicted in the image.

2. The method of claim 1 wherein the width dimension information for the penumbrae is calculated relative to illumination profile information for the image.

3. The method of claim 2 including the further step of identifying linear tokens in the image, and wherein the illumination profile information is determined from the linear tokens.

4. The method of claim 2 wherein the illumination profile information is analyzed to verify correspondence to illumination transitions caused by penumbrae.

5. The method of claim 2 including the further step of fitting the illumination profile information to an illumination model.

6. The method of claim 5 wherein the illumination model comprises a sigmoid model.

7. The method of claim 5 including the further step of using the illumination model to calculate the width dimension information for the penumbrae.

8. The method of claim 1 wherein the processing scale parameter information comprises a processing scale parameter determined as a function of a set of processing scale parameters corresponding to individual penumbra among the penumbrae depicted in the image.

9. The method of claim 1 wherein the processing scale parameter information comprises a set of spatially-varying processing scales.

10. A computer program product, disposed on a non-transitory computer readable media, the product including computer executable process steps operable to control a computer to: provide an image file depicting an image, in a computer memory, calculate processing scale parameter information as a function of width dimension information for penumbrae depicted in the image, and generate, from the image, intrinsic illumination and material reflectance images corresponding to the image using the processing scale parameter information, wherein the intrinsic illumination image represents intensity and color of light incident upon each point on surfaces depicted in the image and the intrinsic material reflectance image represents reflectance properties of surfaces depicted in the image.

11. The computer program product of claim 10 wherein the width dimension information for the penumbrae is calculated relative to illumination profile information for the image.

12. The computer program product of claim 11 including the further process step to identify linear tokens in the image, and wherein the illumination profile information is determined from the linear tokens.

13. The computer program product of claim 11 wherein the illumination profile information is analyzed to verify correspondence to illumination transitions caused by penumbrae.

14. The computer program product of claim 11 including the further process step to fit the illumination profile information to an illumination model.

15. The computer program product of claim 14 wherein the illumination model comprises a sigmoid model.

16. The computer program product of claim 14 including the further step to use the illumination model to calculate the width dimension information for the penumbrae.

17. The computer program product of claim 10 wherein the processing scale parameter information comprises a processing scale parameter determined as a function of a set of processing scale parameters corresponding to individual penumbra among the penumbrae depicted in the image.

18. The computer program product of claim 10 wherein the processing scale parameter information comprises a set of spatially-varying processing scales.

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